STUDENT PERCEPTION OF SCHOOL CLIMATE BEFORE AND DURING THE COVID-19 PANDEMIC

by

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DISSERTATION ABSTRACT

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Title: Student Perception of School Climate Before and During the COVID-19 Pandemic

School climate is comprised of experiences of school life that reflect norms, values, relationships, teaching practices and systemic structures. A student's perception of school climate can be impacted by individual-level (race and gender), school-level (school socioeconomic status, school size, and schoolwide practices), and district-level (institutional policies) factors. There is extensive evidence on the impacts of schoolwide supports such as Positive Behavioral Interventions and Supports (PBIS) on school climate. Specifically, there is a robust body of literature suggesting that fidelity of PBIS implementation is associated with positive school climate outcomes. In March 2020, schoolwide practices were disrupted as a result of the COVID-19 pandemic, where educational practices changed drastically for millions of students. The present study investigates how school-level student perception of school climate changed throughout the COVID-19 pandemic in 195 elementary schools who maintained school climate data through PBISApps (dataset #D0130). All schools were implementing PBIS and assessed school climate data once before and once after the onset of the pandemic. Multilevel modeling with piecewise time covariates was conducted to examine changes in school climate from the 2018-2019 (Time 1) to the 2021-2022 (Time 4) school year. Results suggested a statistically significant increase during the 2020 – 2021 school year, followed by a statistically significant decrease during the 2021 – 2022 school year. Results also showed a negative association between the percent of students receiving free and reduced lunch and a school's overall student perception of school climate. Limitations of this study include the sample composition, possible inaccuracies of demographic data, and school modality of instruction. Findings from this study outline the importance of school climate assessment data and indicators that promote fidelity in implementation. Recommendations to support school assessment procedures are discussed.

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CHAPTER I

LITERATURE REVIEW AND INTRODUCTION

School Climate

The National School Climate Council (2007) defines school climate as “the patterns of people/s experiences of school life and reflects norms, goals, values, interpersonal relationships, teaching and learning practices and organizational structures.” For this study, school climate will be conceptualized through a Bio-Ecological framework, where an individuals’ behavior and perspective relate to their experiences with other individuals, the environment, and the interaction between these systems (Bronfenbrenner, 1979; Wang & Degol, 2016). According to this perspective, there are four essential domains that contribute and shape school climate: Safety, Teaching and Learning, Relationships, and Environmental-Structural (Cohen et al., 2009; Thapa et al., 2013).

As summarized by Cohen and colleagues (2009) and Wang and Degol (2016), Safety is an essential domain that is comprised of physical and socio-emotional safety, referring to a student’s perception of safety, as influenced by the presence of violence and aggression, staff response to bullying, and availability of caring staff. Teaching and Learning contributes to the educational environment of school climate through four subdomains that include, quality of instruction, social-emotional learning, professional development, and leadership. Overall, this domain incorporates teacher behaviors and instructional practices that happen within the classroom, along with schoolwide systemic practices and norms. The Relationship domain of school climate is comprised of three subdomains, including respect for diversity, school community and collaboration, and morale and connectedness. Each subdomain of relationships outlines interactions of equitable actions, relationships between students and teachers, and sense of community. Finally, the Environmental-Structural domain incorporates the physical school environment, including the space, organization and cleanliness. Each domain of school climate offers a unique contribution to a school's overall culture, as research has supported that aspects of each domain support student educational experiences and their outcomes (Cohen et al., 2009; Thapa et al., 2013; Wang & Degol, 2016). Although each of these domains describe various aspects of school climate, school climate as a whole encapsulates the quality of school life, considering typical goals, beliefs, values, interactions between peers and staff, and the educational structure of the school (Cohen et al., 2009; La Salle, 2020).

Factors that Influence School Climate Perceptions

Student-Level

While student experiences within each domain are likely to change their overall perception of school climate, student perceptions are also influenced by individual, school, and district-level factors. In general, students' perception of school climate may be shaped by individual demographic information (Koth et al., 2008). A student's grade level status and age may influence their perception of their educational experience, as students in earlier grades typically report a more positive perception of school climate (La Salle, 2020; Wang & Degol, 2015). When considering gender, research has documented that boys tend to have a more negative perspective of school climate (Buckley et al., 2003). Specifically, Fan and colleagues (2011) found that male students perceived school rules to be less fair and teachers to be less supportive compared to their female student peers.

Additionally, having a marginalized identity on the basis of race, ethnicity, gender, and ability may also relate to perception of school climate. For instance, students with a marginalized gender identity (i.e., transgender or nonbinary students) have self-reported a less positive perception compared to male and female cisnormative identifying students (Colvin et al., 2019; La Salle, 2020). Students with a marginalized sexual identity have also been found to report less positive perceptions of school climate compared to non-LGBTQ peers (La Salle, 2020). Along with gender and sexual identity, those with a marginalized racial/ethnic identity often report more negative perceived school climate compared to white peers (Parris et al., 2018; Watkins & Aber, 2009). Fan and colleagues (2011) also found that school perception varied by racial identity, with Latino/a/x (from now on referred to as Latine) and Asian identifying students reporting worse ratings of safety, whereas other races reported a less positive perception of positive teacher-student relationships. Finally, disability status may also impact perceptions of school climate, as students with emotional and behavioral difficulties may have more negative perceived ratings of school climate compared to students without disabilities (La Salle, 2018). In summary, studies suggest that student perception of school climate may be influenced by individual level factors, such as gender and sexual identity, racial/ethnic identity, and disability status.

School-Level

Research has suggested that school-level factors such as quality of student-teacher relationships and principal turnover were closely associated with student perception of school climate (Koth et al., 2008; Mitchell et al., 2010). Other factors such as school size may also contribute to students' perception of school climate, as Cotton's (1996) review found that elementary schools with a smaller number of students may have positive benefits. These results, in addition to class size, were further supported by Koth and colleagues (2008). Similarly to individual-level marginalized identities, schools serving a larger proportion of marginalized students have a lower average perception of school climate (Jain et al., 2015; Parris et al., 2018).

When looking at the relations between school socioeconomic status (SES), one study found that students attending a low SES school felt less safe at school (Ruiz et al., 2018). This is consistent with a review of studies that found school SES to be negatively associated to school climate (Stevenson, 2006).

Along with both individual and school-level factors, district-level practices may also influence school climate. Researchers have found that district-level initiatives and policies may improve student perception of school climate at the school level. In a systematic review of literature, Ascorra and colleagues (2019) reviewed 34 articles and found six strategies to improve school climate at the district level. Specifically, strategies that involved creating a district-university partnership, implementing positive and protective district policies, creating a positive district climate, implementing interventions at schools through district initiatives, and developing strategies for accountability may create a positive school climate at the school level. Additionally, Bosworth and colleagues (2018) found that there was a possible influence of district-level leadership on school-level team functioning, however more research is needed to support this finding.

Overall, the importance of individual-level, school-level and district-level factors should not be ignored, as variables such as school composition of gender and racial identity, school size and school SES may influence the overall perception of school climate. Additionally, district-level school policies, interventions and overall district culture may also contribute to students' perception of school climate. In order to assess the role and impact of these compounding influences on student perception of school climate, researchers advocate for the use of multilevel modeling to account for variance based on individual-level, school-level, and district-level factors (Wang & Degol, 2016).

Importance of School Climate on Student Outcomes

Academic Outcomes

A positive school climate is related to a plethora of positive academic, behavioral, and mental health related outcomes (Aldridge & McChesney, 2018; Thapa et al., 2013; Tubbs & Garner, 2008: Wang & Degol, 2016). Academically, a positive school climate has been related to higher academic engagement (Daily et al., 2019; Konold et al., 2018). Additionally, those with a more positive perception of school climate self-reported higher grades and future academic aspirations such as the desire to attend post-secondary education (Shukla et al., 2016). At the school level, a positive school climate has been shown to moderate the relation between low academic achievement and low SES (Berkowitz et al., 2017). A positive school climate may also relate to schoolwide implementation of equitable practices, as schools with more positive school climates reported smaller differences in self-reported grades between those with a marginalized racial identity and White students (Jones & Flemming, 2021).

Behavioral and Mental Health Outcomes

Behaviorally, a positive school climate has been shown to increase positive behaviors, decrease negative behaviors, and play an important part in the prevention of student problem behaviors and student discipline (Dorio et al., 2020; Reaves et al., 2018; Wang et al., 2010). More specifically, a positive school climate has been related to an increase in prosocial behavior (Hopson et al., 2014) and higher school attendance (Daily et al., 2020; Hamlin, 2021). A positive school climate has also been linked to a reduction of bullying victimization and delinquent behaviors (Aldridge et al., 2018), and a decrease in office discipline referrals (Huang & Cornell, 2018). Lastly, school climate has been related to preventing risky and bullying behaviors in youth at risk (Klein et al., 2012; Low & Van Ryzin, 2014; Wang et al., 2013).

A positive school climate may also relate to better social-emotional outcomes for students, particularly for students with increasing mental health concerns (Aldridge & McChesney, 2018; Colvin et al., 2019; La Salle, 2021). In Aldridge and McChesney's (2018) review of the literature, the authors state that a variety of school climate domains are related to increases in psychosocial wellbeing and decreases in mental health concerns. Additionally, a positive school climate was found to be associated with lower rates of depression and suicidal ideation for foster children, and school-attendance issues among unhoused youth (Moore et al., 2018; Shim-Pelayo & Tunac De Pedro, 2018). School climate has also been shown to moderate the impact of sexual harassment and cyber victimization on student wellbeing, with more positive experiences at school being typically associated with lower levels of depressive or internalizing symptoms (Crowley et al., 2021; Holfeld & Baitz, 2020; Zhao et al., 2021).

Importance of Elementary Student Perception of School Climate

Many of the studies examining student outcome data focus on secondary schools (i.e., middle and high school) and secondary students as participants (Wang & Degol, 2015). Educational experts have discussed the importance of prevention efforts at mitigating risk for negative outcomes and promoting positive practices to meet students' needs early in their educational experiences (Domitrovich et al., 2010; Horner et al., 2010). Researchers have promoted the need for examination of school climate at the elementary level, such as using elementary student voice to assess school climate (La Salle et al., 2016) and including longitudinal studies to investigate how elementary student perception may change over time (Wang & Degol, 2016). Within the elementary school population, male students, students from a minoritized background, and students in older elementary grades reported a less positive perception of school climate (La Salle, 2016). Elementary student perception of school climate has been positively related to academic achievement (Ruiz et al., 2018), and student engagement (Yang et al., 2018). One longitudinal study found that a positive school climate in elementary school is related to a more positive social and academic self concept in middle school (Coelho et al., 2020). Thus, student perceptions of school climate within the elementary context may highlight unique indicators of student experiences that may be important targets for prevention efforts through a multi-tiered system of support.

Multi-tiered Approaches to Improving School Climate: Role of PBIS

Multi-tiered systems of support (MTSS) is the integration of a multi-tiered system where instruction, assessment and decision-making are matched to student academic and behavioral need. Within MTSS, positive behavioral interventions and supports (PBIS) is an evidence-based framework that supports the implementation of behavioral practices (McIntosh & Goodman, 2016). PBIS is a range of interventions and practices, housed within three tiers of intervention; Primary Intervention, Secondary Intervention, and Tertiary Intervention (Horner et al., 2010). Primary Intervention (Tier 1) is further defined as practices that are used for all students, whereas Secondary Intervention (Tier 2) and Tertiary Intervention (Tier 3) provide more targeted and intensified support (Horner et al., 2010). These practices ensure that students receive added intensified support based on need (Sugai & Horner, 2009).

When focusing on Tier 1 supports, the core features of PBIS include the creation of a leadership team, consistent and regular routines and scheduling, a commitment for a positive school climate, data-based monitoring and evaluation, and procedures for training and coaching new personnel. Additionally, there are five core Tier 1 practices including defining school expectations, matching expectations with social-emotional and behavioral skills, acknowledging appropriate behaviors, responding instructionally to unwanted behaviors, and using data for decision making (Center on PBIS, 2022b). Currently, over 25,000 schools implement PBIS throughout the United States (Center on PBIS, 2022b).

Effects of PBIS on Student Outcomes

Academic and Behavioral Outcomes

A meta-analysis of the positive outcomes related to PBIS implementation found that high fidelity of PBIS implementation had a positive effect on student academic outcomes (Lee & Gage, 2020). Some studies found that high fidelity of implementation was associated to higher student achievement (Madigan et al., 2016; Pas & Bradshaw, 2012), whereas other researchers found that there was a positive association with student achievement only after PBIS had been implemented for more than 3 years (Kim et al., 2018).

The benefits of high fidelity of PBIS implementation also positively impact student-level and school-level behavioral outcomes (Lee & Gage, 2020). Research indicates that schools with higher fidelity of implementation have lower student truancy rates (Pas & Bradshaw, 2012; Pas et al., 2019). Other studies have suggested that schools with high fidelity of implementation had lower rates of office discipline referrals and out of school suspensions (Elrod et al., 2022; Grasley-Boy et al., 2019; Kim et al., 2018; Lee et al., 2021; McIntosh et al., 2021; Noltemeyer et al., 2019; Simonsen et al., 2021), whereas others did not (Childs et al., 2016). In some studies where this relation was not found, the authors mentioned how state-wide and district-level policies and initiatives may have altered non-PBIS practices (Pas & Bradshaw, 2012).

School Climate Outcomes

High PBIS fidelity of implementation has also been related to positive effects on school climate and organizational health (Lee & Gage, 2020). Overall, the positive relation between adequate implementation of PBIS and school climate has been documented in research

(Bradshaw et al., 2009; Ellis et al., 2022; Elrod et al., 2022), with PBIS being one of the most effective school wide interventions known to improve school climate (Charlton et al., 2021). For example, Elrod and colleagues (2022) found that in a three-year longitudinal study, middle and high schools implementing PBIS with fidelity saw a statistically significant average increase of 0.15 on the Georgia Brief School Climate Inventory each year. This study also that for each year of prior implementation, there was an average increase of .11 on the Georgia Brief School Climate Inventory. Along with an increase in student-level perception of school climate, Bradshaw and colleagues (2008a) found that schools that implemented PBIS saw improvement on a measure of overall organizational health (i.e., perception of staff relationships, student behavior and administrative support), as well as resource influence (ability to receive allocation from district resources), and positive relationships between staff and students. Additionally, compared to non-PBIS schools, teachers in schools implementing PBIS responded more positively to questions regarding school leadership and student behavior management. Teachers in schools with high PBIS fidelity of implementation also responded more positively to questions regarding schoolwide expectations, student conduct, and school safety, compared to teachers in schools with moderate or low fidelity of PBIS implementation (Houchens et al., 2017).

Overall, the implementation of PBIS appears to have a positive influence on organizational functioning and school climate. Additionally, there is support that PBIS positively influences behavioral and academic outcomes. Some studies have identified that the absence of student and school-level findings may be explained through state-level policy and educational initiatives. Notably, schools with high fidelity of implementation have higher perception of systems organization and more positive student outcomes than those with moderate or lower fidelity of implementation.

PBIS Fidelity of Implementation

Although thousands of schools implement PBIS, it is important for schools to receive continued professional development, as these practices are more consistently implemented with training (Bradshaw et al., 2008). Meeting fidelity of implementation may be difficult, as some statewide reports indicate about half of the schools implementing PBIS meet adequate fidelity of implementation (Jorgenson & Boezio, 2012). When considering the implementation of PBIS, elementary schools were more likely to meet adequate fidelity of implementation sooner than middle and high school settings, with an average time to adequate implementation being 2 years, compared to 2.4 years and 3 years (Nese et al., 2019). Additionally, non-Title 1 elementary schools were more likely to meet adequate implementation the fastest at 1.82 years (Nese et al., 2019).

Trends of School Climate before COVID-19

The Georgia Elementary School Climate Survey (Center on PBIS, 2022), has been utilized in research spanning over a decade (Center on PBIS, 2022; La Salle et al., 2016). In the initial publication of the Georgia Elementary School Climate Survey, elementary students indicated an average school climate rating of 3.22 (on a scale of 1 to 4) during the 2013 - 2014 school year (La Salle et al., 2016). In a follow up publication, elementary students indicated an average school climate rating of 3.12 during the 2017 - 2018 school year (La Salle, 2020), indicating that there was a stable trend in perception of school climate. Although with different populations, both studies indicate that average student perception of school climate remained slightly above a three out of four during these four years.

However, over the past five years, data from the California Elementary School Climate Report Card (2022) reflects a worsening perception of school climate in many of the school climate domains between 2018 and 2020. These domains include School Connectedness, Academic Motivation, Caring Relationships, High Expectations, Meaningful Participation and Perceived School Safety, Low Violence Victimization, Fairness, Positive Behavior, and Parent Involvement. The School Connectedness, Caring Relationships and High Expectations domains measure a students' perception on feelings of closeness and relationships within the school. The Academic Motivation domain assesses completion and resiliency of academic tasks, while the Meaningful Participation domain measures a student's perception of choice and engagement within schoolwide and class specific contexts. The School Safety and Low Violence Victimizations domains measure a student's perception of safety and occurrence of victimization/bullying. The Fairness domain assesses an individual's perception of being treated fairly by staff and the fairness of school rules, while the Positive Behavior domain assesses compliance to school rules and expectations. Lastly, the Parent Involvement domain measures the occurrence of parent (or another adult at home) taking interest and supporting schoolwork.

Specifically, between 2018 and 2020 there was a 22% decline in School Connectedness, a 14% decline in Academic Motivation, a 15% decrease in Caring Relationships, a 10% decrease in High Expectations, a 5% decrease in Meaningful Participation, a 28% decrease in School Safety, a 13% decrease in Low Violence Victimization, a 12% decrease in Fairness, a 10% decrease in Positive Behavior, and a 6% decrease in Parent Involvement (California Survey System, 2022).

Trends of PBIS Fidelity of implementation before COVID-19

Over the past five years, many states have created statewide reports regarding PBIS fidelity of implementation. Florida reported that adequate PBIS implementation was positively trending from 2017 to 2019, with 83% of schools implementing PBIS with fidelity (Florida

PBIS, 2019; Florida PBIS, 2020; Florida PBIS, 2021). Nevada's PBIS Technical Assistance Center (2022) also published yearly results from a federally funded school climate grant. Before the project, during the 2017- 2018 school year, Nevada had 37% of schools implementing Tier 1 adequately. By the 2019-2020 school year, the percentage of schools implementing PBIS adequately increased to 57%. Lastly, Missouri has published annual reports regarding state-wide engagement with PBIS. From 2017-2019, the state of Missouri maintained a high percentage (about 90%) of schools implementing PBIS adequately (Missouri School Wide Positive Behavior Support, 2017; Missouri School Wide Positive Behavior Support, 2018; Missouri School Wide Positive Behavior Support, 2019, Missouri School Wide Positive Behavior Support, 2020; Missouri School Wide Positive Behavior Support, 2021).

In summary, states that published annual reports found an increase in the percentage of schools meeting adequate fidelity of implementation up until the 2019-2020 school year and the start of the COVID-19 pandemic.

Effects of COVID-19 on Student Outcomes

In March 2020, all 50 states closed schools temporarily for the SARS-CoV-2 (COVID-19) pandemic, impacting almost 57 million school aged youth. These closures may have reduced spread and mortality of COVID-19; however, research found that these closures impacted economic productivity, a decrease in work hours, decreased health care and other supports for students (Donohue & Miller, 2020). Although the impact of the COVID-19 pandemic reaches much farther than education, as evidenced by increases in parental stress, increased mental health concerns in children and adults, and financial instability (APA, 2020; Chen et al., 2022; Fong & Iarocci, 2020; Russell et al., 2020), the following review will focus on changes within educational contexts after the onset of the COVID-19 pandemic. The focus on educational literature in this review does not eliminate the influence of these negative changes on students, families, and the overall educational system.

As summarized by Middleton (2020), many schools had to abruptly change modality of instruction to a virtual format without preparation or training. In response to distance learning environments, 92% of teachers indicated that they had never taught online, and teachers perceived this transition to digital learning to be difficult, with only half of teachers expressing some preparation to deliver remote instruction (Marshall et al., 2020). It was estimated that 19% of students received fully in-person instruction during the start of the 2020-2021 school year, while 20% received hybrid instruction and 60% received all remote instruction (Dorn et al., 2020). This trend varied over the next eight months, as schools and districts altered their instructional modality over time. In March 2021, a majority (57.1%) of districts delivered in-person instruction, while 20.6% delivered hybrid instruction, 11.3% delivered varied instruction and 10.7% delivered remote only instruction. Of these schools, 71.8% of rural districts delivered in-person instruction, compared to 30.2% of suburban districts and 28.2% of city districts (Center on Reinventing Public Education, 2021). Along with a high variation of modality, research has estimated that about 30% percent of students lack adequate internet or devices needed to engage with remote instruction (Chandra et al., 2020). Additionally, it is estimated that only 32% of remote instruction meets above average instructional practices (Dorn et al., 2020).

Changes in Student Outcomes during the COVID-19 Pandemic

Academic, Behavioral, and Mental Health Outcomes

Not surprisingly, large-scale instructional changes (i.e., modality of instruction) and school closure throughout the pandemic significantly impacted student academic, behavioral and mental health outcomes, as well as systems functioning. Academically, the National Assessment of Educational Progress 2022 Long-Term Trend Highlights Report indicated that in the past year, reading scores had the largest decrease since 1990, and mathematics scores had the largest decrease ever documented by the National Center for Education Statistics (U.S. Department of Education, 2022). This has been supported throughout literature, as studies in reading and math found similar declines in student achievement (Domingue et al., 2021; Kuhfeld et al., 2022). Research has also found that historically marginalized students (Black, Latine and Native American), and lower achieving districts, showed larger declines in mathematics and reading (Bailey et al., 2021; Domingue et al., 2021; Kuhfeld et al., 2022; Lewis & Kuhfeld, 2021).

Research and practice has documented a decrease in student attendance (Carminucci et al., 2021; Nevada PBIS, 2022). Additionally, exclusionary discipline also declined, which may be part of remote learning practices (Welsh et al., 2022). Alongside changes in behavioral outcomes, elementary student wellbeing may have changed, as COVID-19 lockdowns and school closures have been related to an increase of mental health concerns for youth between the ages of 1 and 19 (Hawrilenko et al., 2021; Panchal et al., 2021) Modality of instruction may also be related to elementary and middle school student mental health, as students with fully remote instruction had the lowest perception of mattering at school (Verlenden et al., 2021).

School-Level Outcomes

School systems have had a variety of experiences maintaining instructional functioning, with one research study noting that 20% of schools had persistent dysfunction or a low return to school functioning during the pandemic. Examples of school dysfunction include delayed academic support, as technological devices were given to families two months after school closure (Supovitz & Manghani, 2022). Additionally, dysfunction occurred in policy, as grading policies accidently discouraged attendance or placed minimal incentives on students to attend.

District policies may have also resisted closure until state mandates, therefore reducing valuable preparation time (Supovitz & Manghani, 2022).

As for PBIS fidelity of implementation, Florida reported a 5% reduction of schools that met adequate implementation during 2021 (Florida PBIS, 2021, Florida PBIS, 2020). Along with a reduction of schools implementing PBIS adequately, the number of schools that submitted fidelity data decreased by 30% during the 2019-2020 school year. Similarly, Missouri reported a 3.5% decrease in adequate implementation of schools. The number of schools in Missouri reporting implementation data severely decreased, as 38% completed the Tiered Fidelity Inventory Tier 1 scale in 2019-2020, a 20% reduction from the previous school year (Missouri School Wide Positive Behavior Support, 2021). Neither report outlines how fidelity of implementation varied by modality of instruction, so it is unknown whether decreases in fidelity submission or scores were related to modality.

Literature Review Summary and Research Gaps

School climate is important, as it has been significantly associated with key student academic, behavioral, and mental health outcomes across elementary and secondary school-age populations (Aldridge & McChesney, 2018; Thapa et al., 2013; Wang & Degol, 2015). When implemented with a high fidelity of implementation, PBIS has shown positive impacts relating to school climate, as well as academic and behavioral student outcomes (Lee & Gage, 2020). Many studies descriptively reported educational changes during COVID-19, all of which found a decrease in elementary student academic achievement (in both reading and mathematics), changes in student behavior (such as a decrease in attendance), and an increase in elementary student mental health concerns (such as an increase in risk for depression and anxiety;

Carminucci et al., 2021; Domingue et al., 2021; Panchal et al., 2021; U.S. Department of Education, 2022).

Although statewide reports have identified a decline in the percent of schools meeting PBIS fidelity of implementation during the COVID-19 pandemic, research has yet to investigate these trends in detail, especially in elementary schools. Given the discussed importance of school-based prevention and the longitudinal impact of a positive school climate on students social and academic self-concept, it is important to investigate potential changes in early school experiences. Although more is known regarding secondary students, published research has not yet investigated how elementary student perception of school climate may have changed during the COVID-19 pandemic.

Current Study

Using a national-level elementary school sample, the current study aimed to investigate how ratings of school climate have changed throughout the COVID-19 pandemic. One of the study's main goals was to explore how student perceptions of school climate may have changed from pre-pandemic schooling (2018 – 2019 or Fall of 2019 – 2020) to the onset of the COVID-19 (2020 – 2021), and year two of the pandemic (2021-2022). Additionally, this study sought to understand how individual (i.e., race and gender) and school level factors (i.e., school size, locale, school SES and pre-pandemic PBIS fidelity of implementation) may be associated with changes in school climate, as previous research has identified these factors as potential influences in student perception of school climate. This study utilized multilevel modeling to answer the following research questions.

Research Question 1: What was the average student rating of school climate the year before the COVID-19 pandemic (2018 – 2019 and Fall of 2019 – 2020), and what was the change during year one (2020 – 2021) and year two (2021 – 2022) of the COVID-19 pandemic?

Research Question 2: To what extent did initial level and change in student school climate perceptions during the COVID-19 pandemic vary based on school characteristics (i.e., race, gender, socio-economic status, locale and school size)?

Research Question 3: To what extent did change in student school climate perceptions during the COVID-19 pandemic vary based on pre-pandemic PBIS fidelity of implementation?

Hypothesis 1: With current academic, behavioral and socio-emotional research highlighting negative educational consequences of the pandemic (U.S. Department of Education, 2022, Panchal et al., 2021), it was hypothesized that student perception of school climate will decrease during the 2020-2021 school year and increase to near pre-pandemic levels during the 2021-2022 school year.

Hypothesis 2: Consistent with current literature documenting how race, socioeconomic status and school size are related to school climate (Koth et al., 2008; Ruiz et al., 2018; Thapa et al., 2013), it was hypothesized that historically marginalized populations, those coming from large schools, and schools serving a higher percentage of students receiving free and reduced lunch will have a lower initial level perception of school climate.

Hypothesis 3: Prior research has established positive links between the implementation of PBIS and student perception of school climate (Bradshaw et al., 2008b; Charlton et al., 2021; Hauchens et al., 2017). It was hypothesized that schools with adequate PBIS fidelity of implementation will have a more positive perception of school climate compared to those without adequate PBIS fidelity of implementation.

CHAPTER II

METHOD

Participants and Settings

Participants were included from a sample of 195 public elementary schools. This study aims to investigate elementary schools due to prior advocacy from research (La Salle, 2016; Wang & Degol, 2015), and the importance of prevention through promoting positive school practices (Domitrovich et al., 2010; Horner et al., 2010). Schools were included in this sample if they a) were identified as a public elementary school serving any grades from kindergarten through sixth grade, b) reported school climate data through Educational and Community Supports (ECS) data collection, c) reported school climate data in at least one year immediately pre-pandemic (2018 – 2019 and/or 2019 – 2020) and at least one year after the onset of the COVID-19 pandemic (2020 – 2021 and/or 2021 – 2022), and d) had 20 or more school climate surveys (i.e., 20 or more students) completed per each year.

Initially, 614 schools serving students up to Grade 6 reported school climate data between the 2018 – 2019 and 2021 – 2022 school years. Of these schools, 402 schools were eliminated from the sample as they did not report school climate once before and after the onset of the pandemic. Therefore, 212 were retained. After removing schools with missing demographic data, 209 schools were retained in the sample. Lastly, 14 schools were removed from the sample for having fewer than 20 school climate surveys completed during any of the four school years, leaving a final sample of 195 schools. A subsample of 132 schools reported TFI data during the 2018-2019 school year.

The final study sample included 195 schools from 66 districts, 35 of which had only one participating school. One district had 18 schools; the remaining districts fell in between. Schools were in 14 different states. The states with the highest number of schools represented in the sample were Michigan (60) and California (58), followed by Missouri (16), Maine (14), Oregon (11), Virginia (11) and Nebraska (8). The remaining states had 5 or less schools in the sample; Arizona had 5, Wisconsin had 4, and Minnesota, Montana, and Ohio had 2. Vermont and Washington had only 1 school each. Michigan and California were among the largest proportion of schools represented in the current study sample which is not surprising given that these schools most widely implement PBIS and assess school climate with PBIS Apps, and therefore are not considered to be overrepresented in the sample. Table 1 (Appendix A) summarizes descriptive demographic statistics for the present study.

Measures

School-Level Demographics

Demographic data were obtained through the NCES Common Core of Data database. The ELSI Table Generator (https://nces.ed.gov/ccd/elsi/tablegenerator.aspx) was used to compile school level demographic information during the 2018 – 2019 school year. Information compiled included school state, total enrollment, school- level racial composition (total number of Black or African American, American Indian/Native American, Latine, Native Hawaiian, multiracial and White racial identity students), number of students receiving free or reduced lunch, total number of male students, and school locale. School-level student data such as gender identity, racial and ethnic identity, and status of free or reduced lunch represent student characteristics aggregated at the school-level and do not represent individual student experiences. Data for the lowest and highest grade served at the school was also obtained.

School Climate

Elementary school student perception of school climate was assessed using the Georgia Elementary School Climate Survey (Appendix P: Center on PBIS, 2022; La Salle et al., 2016). This is an 11-item measure ranging from a 1 – 4 Likert scale (Never – Always). This measure has been used in multiple studies (La Salle et al., 2016; La Salle et al., 2018; La Salle, 2020) and has a documented internal consistency of .8 (La Salle et al., 2018), along with acceptable construct validity based on goodness of fit statistics (Martinelli & Raykov, 2021). A factor analysis indicated one main factor, with factor loadings ranging from .315 to .658 (La Salle et al., 2016). Overall, this measure has evidence of acceptability through prior research, acceptable internal consistency and construct validity (Martinelli & Raykov, 2021).

PBIS Fidelity of Implementation

Fidelity of implementation was assessed using the PBIS Tiered Fidelity Inventory (TFI; Algozzine et al., 2014). The TFI (Appendix Q) has fidelity of implementation scores for Tier 1, Tier 2, and Tier 3; however, this study used only Tier 1 fidelity of implementation data. The TFI Tier 1 scale has 15 items. Each item is scored using a 0-to-2-point system, wherein 0 represents not implemented, 1 represents partially implemented, and 2 represents fully implemented. The TFI has evidence of strong internal consistency (.96), strong content validity across all three tiers (.95), strong ratings of usability, strong interrater reliability (.99) and strong test-retest reliability (.99; McIntosh et al., 2017).

Procedures

School-Level Demographics

Demographic data accessed through the ESLI Table Generator for the 2018 – 2019 school year was merged in R to school-level climate data through the use of NCES school identification numbers. NCES school-level demographic racial data reported zeros as a dash, and all dashed racial variables were replaced with a zero. To ensure dashed data represented a zero, the total number of student racial demographics within a school (including white and minoritized students) was summed and compared to school total enrollment. These values matched 100% of the time, supporting that the dashed lines represented zero. Alongside school-level racial composition, school locale was condensed into the broader urban, suburban, and rural categories. NCES locale data has 12 subcategories within urban, suburban, and rural areas. Schools in urban areas were operationalized as any previous NCES category that included the word “City”. Schools in suburban areas were operationalized as NCES categories that included the word “Suburban” and rural areas were operationalized as categories that included words such as “Town” and “Rural”. Town and Rural locales were collapsed together due to a small number of schools (24) located in a “Town” locale. Dichotomous variables were created for Suburban and Rural schools, where 1 indicated that the school fit that locale, and 0 indicated the school fit another locale.

After demographic data had been cleaned, percentage variables were calculated for the percent of male students, the school-level percent of students receiving free or reduced lunch, and the school-level percent of minoritized students. The school-level percent of male students was calculated by dividing the number of male students over the school’s total enrollment, multiplied by 100. The percent of student receiving free or reduced lunch was calculated by dividing the number of students receiving free or reduced lunch by the school’s total enrollment, multiplied by 100. Additionally, the school-level composition of percent of minoritized/marginalized students was calculated by adding the total number of Black or African American, American Indian/Native American, Latine, Native Hawaiian, and multiracial identity students, divided by the school’s total enrollment, multiplied by 100. School total enrollment, percent of male students, percent of students receiving free or reduced lunch, and school-level percent of minoritized students were all grand mean centered.

School Climate

The school average student perception of school climate was accessed through the maintenance of PBISApps by the Educational and Community Supports (ECS) research unit at the University of Oregon. Data was collected via the web application PBIS Assessment (http://www.pbisapps.org/pbis-assessment). This database is housed and managed at ECS through a data repository. School climate scores were operationalized as the school-year average score per item, therefore taking the total number of points divided by 11. The school-year average may include multiple administrations, however dataset #D0130 does not specify which schools had multiple administrations. School climate scores were not centered and were operationally defined as yearly school-level average. There were no item-level missing data.

Scores were collected at any timepoint during each school year (Fall – Spring). The end date of survey administration represents when the climate survey closed for the year. Schools may have had multiple administrations before data collection was closed for that year. During the 2018 – 2019 school year, survey completion ranged from August 29th, 2018 to June 14th, 2019. Data collection during the 2019 – 2020 school year was limited during the pandemic, with survey completion ranging from August 17th, 2019 to April 1st , 2020. School climate survey completion started later during the 2020 – 2021 school year, ranging from October 6th, 2020 to June 14th, 2021. This trend continued into the 2021 – 2022 school year as survey completion ranged from October 8th, 2021 to July 14th, 2022. The most common months of data collection during the 2018 – 2019, 2019 – 2020, and 2021 – 2022 school years were October and November, as the proportion of schools completing school climate administration during October and November were roughly 48%, 69%, and 48%, respectively. Time of survey administration during the 2020 – 2021 school year was more varied, with the most common months of administration being May (21%), followed by November (17%).

PBIS Fidelity of Implementation

PBIS fidelity of implementation is accessed through the maintenance of PBIS Apps via by the Educational and Community Supports (ECS) research unit at the University of Oregon. Data was collected via the web application PBIS Assessment. This database is housed and managed at ECS through a data repository. For this study, the highest score on the TFI during the 2018 – 2019 school year represented the school's pre-pandemic PBIS fidelity of implementation. Only Tier 1 data was included in this study. PBIS fidelity of implementation was operationalized as meeting adequate fidelity of implementation (receiving 70% or more possible points on the TFI; Algozzine et al., 2014). A dichotomous variable was created indicating if a school met adequate fidelity of implementation (1), or if a school did not (0). There were no item-level missing data.

School Year

Student perception of school climate from the 2018 – 2019 (pre-pandemic), 2019 – 2020 (pre-pandemic), 2020 – 2021 (COVID year 1) and 2021 – 2022 (COVID year 2) school years were included in this study. 2019 – 2020 was operationalized as pre-pandemic, as all school climate surveys were completed prior to the end of March 2020. For the analytic model, school year was first centered at zero. Piecewise variables were created to detect the change during each year. A pre-pandemic piecewise variable was created by assigning a zero for the 2018 – 2019 school year, and a one for the remaining school years. A COVID year one piecewise variable was created by assigning a zero to the 2018 – 2019 school year, and the 2019 – 2020 school year, and a one for the remaining two years. A COVID year two piecewise variable was created by assigning a zero to the 2018 – 2019, the 2019 – 2020, and the 2020 – 2021 school year, and a one for the remaining 2021 – 2022 school year.

Analytic Plan

The use of multilevel modeling to analyze nested data has been advocated by school climate researchers (Fan et al., 2011; La Salle et al., 2016; Wang & Degol, 2016). Analyses and all data procedures were conducted in R Version 4.2.2 (2022-10-31) using R Studio (Version 2022.12.0+353) and the *Tidyverse* package (1.3.2; Wickham et al., 2019).

Descriptive Data and Correlations

Descriptive data were calculated in R using the "describe" function in the *Psych* (2.2.9) package (Revelle, 2022). Pearson correlations were calculated using the "ggpairs" function in the *GGally* (2.1.2) package (Schloerke et al., 2021).

Missing Data

To explore patterns of missing school climate data (i.e., schools having no surveys completed in a given year), the "aggr" function in the *VIM* (6.2.2) package (Kowarik & Templ et al., 2016), visualized patterns of missingness. Once patterns of missingness were visualized, Little's missing completely at random test was conducted through the *naniar* (1.0.0) package (Tierney et al., 2023). To enable further investigation of missing data, categorical variables were created indicating if school climate data was present (1) or missing (0) at each year. These dichotomous values at each year were then concatenated together to create one value within a categorical variable. For example, if a school reported school climate data for all years except for the 2020 – 2021 school year, the school would have a value of "1" for variables noting data was present in 2018 – 2019, 2019 – 2020, and 2021 – 2022. The school would also have a value of

"0" for the 2020 – 2021 school year. When concatenated, the schools value for their pattern of missingness would be "1101." Using the dichotomous and concatenated variables described above, independent *t*-tests and analysis of variance were conducted. Grand mean averages of school climate were compared between pattern of missingness. Additionally, school climate averages for other school years and demographic information were compared for group differences whether the school had data present or missing for each individual year.

Along with analysis of variance and *t*-tests to compare for group differences in school climate scores, analysis of variance with post-hoc Tukey HSD analysis were conducted to identify differences in demographic information for each pattern of missingness. Estimated marginal means were analyzed through the "emmeans" function in the *emmeans* (1.8.4-1) package (Lenth, 2023).

Multiple Imputation

Little's missing completely at random test was significant, $\chi2(20) = 41.10$, $p = .003$. Based on data not missing completely at random, and that missing data was related to covariates, multiple imputation was conducted to potentially reduce bias (McCormick et al., 2013; Wang & Hall, 2010). Analysis with non-imputed and imputed data were compared, as recommended by current research (Grund et al., 2016). Multiple imputation was conducted through the *pan* (1.6; Gründ et al., 2016) and *mitml* packages (0.4-4). The *mitml* package creates a user-friendly way to use the *pan* package and allows for the estimation of pooled estimates between models. The *pan* package uses a Monte Carlo Markov Chain Bayesian technique to estimate imputed data based on observed data. Therefore, missing school climate data was imputed conditional on the data within its own school, and within the patterns of other schools. After imputation, model convergence is assessed through the $\hat{R}$ statistic. The $\hat{R}$ statistic should be below 1.05 for all parameters. Models using imputed data will analyze all 100 imputed datasets and the estimates will be pooled using Ruben's rules (Ruben 1987, as cited by Grund et al., 2016). Along with the $\hat{R}$, the fraction of missing information (FMI) is used to note the number of needed imputations. As samples approach an FMI of .5, roughly 59 imputations are needed for accurate reporting of 95% confidence intervals (Bodner, 2008). Along with the FMI, the relative increase in variance due to nonresponse (RIV), notes the variance that can be attributed to missing data. Therefore, the higher the RIV, the more variance. Imputation for this study will align with current research, as researchers advocate for 50,000 burn-in interactions, with 100 imputed datasets, that are 5,000 iterations apart to impute data without correlations between other imputed datasets (Grund et al., 2016). Imputed data was identified as a categorical variable indicating if data was imputed (1) or present (0).

Model Fit

Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), log likelihood (LogLik), and deviance model fit statistics were used to compare model fit. Bayesian Information Criteria approaches model selection by comparing probabilities of each model to identify a true model, while AIC aims to identify simpler models that could be similar to an unknown true model (Kuha, 2004). Researchers often suggest that both AIC and BIC are taken into consideration (Kuha, 2004). Models with a lower AIC and BIC were considered to have better model fit compared to models with higher AIC and BIC statistics. Alongside AIC and BIC, LogLik and deviance statistics were also used to identify model fit. Models with a higher LogLik were identified as having better model fit, while models with a lower deviance statistics were identified as having better model fit. To identify a statistically significant difference in model fit indices, likelihood ratio tests were performed through the "test_lrt" function in the *performance* package.

Growth Models

Full Sample Model

Multiple two-level growth models were conducted in R using the *lme4* (1.1-31) package (Bates et al., 2022). The full sample model was a two-level (repeated measures within schools) growth model identifying the change in school climate scores throughout the pandemic for all 195 schools included in the final sample, while another model investigated school climate change throughout the pandemic for the 132 schools that reported TFI data during the 2018 – 2019 school year.

Prior to model estimation, multilevel descriptive statistics were calculated using the "multilevel.descript" function in the *misty* (0.4.7) package (Yanagida, 2023). Multilevel descriptive statistics include the overall school climate mean, variance within schools, variance between schools, intraclass correlations, and design effect.

For the full sample model, an unconditional model was conducted to identify the grand mean of school climate across all years. After the unconditional model, time was added through three time-varying covariates. One piecewise covariate indicated a change in slope from timepoint one to timepoint two (pre-pandemic), a second indicated change from timepoint two to timepoint three (COVID year 1), and a third indicated a change from timepoint three to timepoint four (COVID year 2). Once time was added into the model, fit indices of models, such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), log likelihood (LogLik), and deviance, were compared with likelihood ratio tests through the "test_lrt" function in the *performance* package. Random effects were added to the piecewise covariates and tested through the “rand” function in the *LmerTest* (3.1-3) package (Kuznetsova et al., 2020). The unconditional model with time and random effects was compared to the unconditional model through likelihood ratio tests to determine if the addition of time created a significant difference on model fit indices. Effect size was calculated by dividing the estimated coefficient over the square root sum of within group variance and error variance in the model (Fraser et al., 2003).

Once a final unconditional model with time was identified, a conditional model was created by adding school total enrollment, percent of male students, school-level percent of minoritized students, school-level percent of students receiving free or reduced lunch, and locale to the model as predictors of the intercept. The main effect of school composition of the percent of racially and ethnically minoritized students, and the percent of students receiving free or reduced lunch investigates school-level effects and does not reflect individual student perspectives. Once main effects were investigated, interaction effects were added to the model for each predictor and each piecewise covariate. For example, the school-level percent of minoritized students had three interaction effects. One interaction with pre-pandemic change, one with year one pandemic change, and one with year two pandemic change. A final model retained only significant ($p < .05$) or marginally significant ($p < .10$) predictors. The final model equation is specified as:

$$School\ Climate_{ti} = \gamma_{00i} + \gamma_{10i}(PreCovid) + \gamma_{20i}(CovidY1) + \gamma_{30i}(CovidY2) + U_{20i} + U_{30i} + \gamma_{03i}(\%Marginalized) + \gamma_{04i}(\%FRL) + \gamma_{05i}(Suburban) + \gamma_{07i}(Missing\ Data) + \gamma_{27i}(Missing\ Data * CY1) + \gamma_{37i}(Missing\ Data * CY2) + e_{ti} \quad \text{(eq.1)}$$

Longitudinal trajectories were visualized through the “plot_trajectories” function in the *lcsm* (0.3.1) package (Wiedemann et al., 2023), and the “ggplot” function in the *ggplot2* (3.4.0) package (Wickham, 2016). Assumptions (such as linearity, homogeneity of variance, outliers, collinearity and normality of residuals) were assessed using the *performance* (0.10.2) package (Lüdecke et al., 2023).

TFI Subsample Model

An unconditional model with only the schools that reported 2018 – 2019 TFI data was conducted to identify the grand mean of school climate across all years. Similar to the full sample model, time was added through three time-varying covariates. Random effects were then added to piecewise covariates at COVID year 1 and COVID year 2. Models were compared through likelihood ratio tests to assessed differences in model fit. Once a final unconditional model with time was identified, the main effect of PBIS fidelity of implementation was assessed. A conditional model was created by adding the main effect of a dichotomous predictor if the school met (1) or did not meet (0) 70% on the TFI. A final model investigated the main and significant effects of meeting the TFI and each piecewise covariate. The final model is specified as:

$$School\ Climate_{ti} = \gamma_{00i} + \gamma_{10i}(PreCovid) + \gamma_{20i}(CovidY1) + \gamma_{30i}(CovidY2) + U_{20i} + U_{30i} + \gamma_{01i}(Meet\ TFI) + \gamma_{14i}(Meet\ TFI * PreC) + \gamma_{24i}(Meet\ TFI * CY1) + \gamma_{34i}(Meet\ TFI * CY2) + e_{ti} \quad \text{(eq.2)}$$

Robustness Checks and Sensitivity Analysis

Robustness checks including a z-score transformation and a z-score transformation with trimmed data within 2.5 standard deviations on the outcome variable were conducted for both the full sample and TFI sample models. Two sensitivity analysis including an added weight of school enrollment and using all schools that completed more than one survey for each year were conducted for both the full sample and TFI sample models.

CHAPTER III

RESULTS

Descriptive Data and Correlations

Descriptive statistics are shown for school climate scores and the percent of students that completed the school climate surveys across four school years in Table 2 (Appendix B). Additionally, the score on the TFI during the 2018 – 2019 school year are shown.

Descriptive statistics show school-level climate averages increased from the 2018 – 2019 school year (3.14) to the 2020 – 2021 school year (3.22), with a decrease during the 2021 – 2022 school year (3.15). The proportion of students that completed the survey decreased by 15.76% from the 2018 – 2019 school year to the 2020 – 2021 school year, with an increase of 8.23% during the 2021 – 2022 school year. The maximum proportion of students that completed the survey may be over 100% due to changes or inaccuracy of school demographic information. Overall, schools included in the sample had a high average percent of points earned on the TFI (85.40), and a large majority met PBIS fidelity of implementation (88.64%). Only 15 schools did not meet adequate fidelity of implementation.

Pearson correlations were conducted to assess associations between school climate and demographic variables (Table 3, Appendix C). School climate scores were associated across each year, ranging from moderate to large, $r = .47 - .71$. School climate scores from each year were negatively associated with the school-level percent of students receiving free or reduced lunch, with the highest association during the 2018 – 2019 school year, $r(147) = -.39$, $p < .001$, and the lowest association during the 2020 – 2021 school year, $r(143) = -.18$, $p = .035$. School climate scores during the 2019 – 2020 school year had a small association with the school-level composition of the percent of minoritized students, $r(164) = -.17$, $p = .031$, and schools in an urban setting, $r(164) = -.25$, $p < .001$. School climate scores during the 2020 – 2021 school year had a small association to schools in a suburban setting, $r(143) = .17$, $p = .046$.

Missing Data

Table 4 (Appendix D) summarizes school climate by pattern of missingness, while Table 5 (Appendix E) summarizes differences in demographic information. Complete data was the most common response pattern for all four school years. However, only 37% of schools had complete data. Little's missing completely at random test was significant, $\chi2(20) = 41.10$, $p = .003$, indicating that missing and present data had statistically significant differences. The most common pattern of missing data, consisting of roughly 19% of the sample, had missing school climate data only during the first year of the pandemic (missing pattern 1101). Analysis of variance indicated a statistically significant difference in grand mean school climate scores by pattern of missingness, $F(8 , 597) = 4.43$, $p < .001$. Post-hoc Tukey HSD analysis indicated that schools missing data during the 2019 – 2020 and 2021 – 2022 school years, $p = .013$, and schools with missing data during the 2019 – 2020 and 2021 – 2022 had significantly lower grand mean school climate scores than those with complete data, $p = .022$. Other significant differences in grand mean school climate scores are described in Table 4. All significant differences are below $p < .05$.

As summarized in Table 5, analysis of variance indicated statistically significant differences in school total enrollment, $F(8 , 186) = 6.06$, $p < .001$, school-level percent of minoritized students, $F(8 , 186) = 5.96$, $p < .001$, school-level percent of students receiving free or reduced lunch, $F(8 , 186) = 3.35$, $p = .001$, the proportion of schools in urban settings, $F(8 , 186) = 3.32$, $p = .001$, suburban settings, $F(8 , 186) = 5.73$, $p < .001$, and the proportion of schools in rural settings, $F(8 , 186) = 4.42$, $p < .001$. Post-hoc Tukey HSD analysis indicated that schools with missing data only during the first year of the pandemic (missing pattern 1101), had statistically significantly higher total enrollment $p < .001$, higher school-level percent of minoritized students $p = .010$, a higher proportion of schools in suburban $p < .001$ and lower proportion of schools in rural $p = .022$ settings compared to those with complete data (1111). Notably, the 1101 schools had the largest total enrollment, the highest school-level percent of free or reduced lunch students, and the highest proportion of schools in suburban settings. Additionally, schools with a 0110 pattern served a lower proportion of students receiving free or reduced lunch compared to schools with compete data, $p = .009$, and schools with a 1001 pattern had a lower school-level percentage of students coming from a minoritized background, $p = .033$, compared to schools with complete data. Tukey HSD analysis also indicated significant differences between other patterns of missingness. These differences can be seen in Table 5. There were statistically significant differences in the number of total enrollment, the school-level percent of minoritized students and the school-level percent of students receiving free or reduced lunch, and locale. All significant differences shown in Table 5 are below $p < .05$.

Table 6 (Appendix F) summarizes differences in school climate score and demographic information between schools that had data present of missing in each year. Independent samples *t*-tests show those with missing data in 2018 – 2019 served a higher proportion of male students, $t(87.03) = 2.16$, $p = .034$ and a lower school-level percent of students receiving free or reduced lunch, $t(68.15) = -3.20$, $p = .002$ than those with complete data in the 2018 – 2019 school year.

Those with missing data during the 2019 – 2020 school year had significantly lower school climate scores during the 2018 – 2019 school year, $t(44.27) = -3.89$, $p < .001$, the 2020 – 2021 school year, $t(30.68) = -3.85$, $p < .001$, the 2021 – 2022 school year, $t(16.59) = -2.25$, $p =$

.038, and a higher proportion of suburban schools, $t(41.97) = -2.17$, $p = .036$, compared to those with present data.

Schools with missing data during the 2020 – 2021 school year had significantly lower school climate scores during the 2021 – 2022 school year, $t(110.55) = -2.26$, $p = .026$, a higher school total enrollment, $t(81.40) = 4.43$, $p < .001$, a higher proportion of marginalized students, $t(87.879) = 2.18$, $p = .032$, a lower proportion of schools in urban settings, $t(175.83) = -3.54$, $p < .001$, and a higher proportion of suburban schools, $t(100.64) = 3.03$, $p < .003$. Schools with missing data during the 2021 – 2022 school year had significantly lower school climate scores during the 2020 – 2021 school years, $t(92.46) = -2.17$, $p = .033$, and a lower school total enrollment, $t(78.26) = -2.05$, $p = .043$ compared with schools with present data.

Growth Models

Prior to model estimation, multilevel descriptive statistics were calculated. Table 7 (Appendix G) summarizes multilevel descriptive statistics for repeated school climate measures nested within schools. The descriptive statistics for all schools included in the full sample, and the TFI subsample had an average number of timepoints within schools over 3, with a range of 2 to 4 timepoints across the years. Both also had similar variance within schools (0.007) and between schools (0.006 – 0.007). Additionally, both samples had a high intraclass correlation (ICC), and a design effect over 1.5, indicating the necessity for multilevel modeling to account for clustering (Finch et al., 2019; Lai & Kwok, 2015).

Full Sample Models

Unconditional Model

An unconditional model (Model 1, Appendix H) was first conducted to investigate the grand mean of school climate across the years. Through model fit statistic comparison, the unconditional growth model without random effects (Model 2) had better model fit across all model fit indices (AIC = -1331.86, BIC = -1303.90, LogLik = 671.93, deviance = -1343.86) compared to the unconditional model, and a pooled likelihood ratio test supported these comparisons, $F(3, 3966.98) = 12.66$, $p <.001$, RIV = .37. Random effects were tested in five randomly selected models, all of which indicated that the inclusion of random effects at COVID year 1 and COVID year 2 improved model fit (Model 1: $\chi2(6) = 246.42$, $p < .001$; Model 2: $\chi2(6) = 276.5$, $p < .001$; Model 3: $\chi2(6) = 251.98$, $p < .001$; Model 4: $\chi2(6) = 262.78$, $p < .001$; Model 5: $\chi2(6) = 209.23$, $p < .001$). The unconditional model with random effects (Model 3) was then used as a base model for conditional models.

Conditional Model

Main effects were first assessed through a conditional model (Model 4), which found statistically significant main effects for COVID year 1, $p = .001$, COVID year 2, $p = .001$, the school-level percent of minoritized students, $p = .043$, and the school-level percent of students receiving free or reduced lunch, $p = .001$. Being in a suburban setting was not significant, $p = .051$. Comparison of fit indices revealed that Model 4 had better fit indices across AIC, LogLik and deviance (model 3 AIC = -1365.40, BIC = -1314.15, LogLik = 693.70, deviance = -1387.40; model 4 AIC = -1388.07, BIC = -1304.21, LogLik = 712.04, deviance = -1424.07). A pooled likelihood ratio test indicated significantly better model fit, $F(7, 12577.28) = 4.32$, $p <.001$, RIV = .31. After main effects were assessed, Model 5 included main effects and interaction effects of all predictors and each piecewise covariate. Model 5 showed significant main effects for COVID year 1, $p = .003$, COVID year 2, $p = .005$, and the percent of students receiving free or reduced lunch, $p = .001$. The presence of missing data had a significant interaction effect with COVID year 1, $p = .011$, and with COVID year 2, $p = .002$. Comparison of fit indices revealed that model five had better fit indices across AIC, LogLik and deviance compared to Model 4 and a pooled likelihood ratio test indicated significantly better model fit, F(21, 18226.25 = 1.71), p = .022, RIV = .51. The final model retained only significant (p < .05) or marginally significant (p < .10) predictors found in Models 4 and 5. Pooled likelihood ratio tests did not find a statistically significant difference between model 5 and the final model, F(22, 25889.54) = .88, p = .63, RIV = .41.

Significant or non-significant estimates for the school-level percent of minoritized students within a school and the school-level percent of students receiving free or reduced lunch describe school-level main effects. As shown in Table 9 (Appendix I), the final model estimates revealed that school climate scores during the intercept (2018 – 2019 school year) was 3.1335 (95% CI [3.1100, 3.1570]), p = .001. Pertaining to time, estimates indicate that there was not a statistically significant change in school climate during the 2018 – 2019 and 2019 – 2020 (Pre-COVID) school years, p = .353. After the onset of the pandemic, there was a statistically significant increase in school climate scores 0.0659 (95% CI [0.0476, 0.08422]), p = .001 between the 2019 – 2020 and 2021 – 2022 (COVID year 1) school years, followed by a statistically significant decrease in school climate scores of -0.0754 (95% CI [-0.0948, 0.0561]), p = .001, between the 2020 – 2021 and 2021 – 2022 (COVID year 2) school years, when controlling for other predictors in the model. There was an effect size of 0.5226 for COVID year 1 and 0.5979 for COVID year 2.

The school-level percent of students receiving free or reduced lunch was also negatively related to school climate. For each percent higher in a school's composition of the percent of students receiving free or reduced lunch, it is estimated with -0.0018 (95% CI [0.0026, 0.0011]),, p = .001 lower perception of school climate. There was a wide range of the school-level percent of students receiving free or reduced lunch in our sample. A one standard deviation higher school-level percent of students receiving free or reduced lunch would estimate a 0.0445 lower perception of school average school climate. If 100% of the students served within a school received free or reduced lunch, it is estimated that their school climate would be lower by 0.0624 compared to a school serving the average number of students receiving free or reduced lunch. If a school served 0% of students receiving a free or reduced lunch, it is estimated that school climate would be 0.118 points higher than the average school-level number of students receiving free or reduced lunch. Serving one standard deviation more or less in school-level percent of students receiving free or reduced lunch had a 0.3529 effect size.

Along with school demographic predictors, a dichotomous variable for main and interaction effects of missing data was retained in the model. The main effect of missing data was not significant, $p = .268$; however interaction effects indicated a significant change in slope during COVID year 1 and COVID year 2 for those with missing data. When missing data was present during COVID year 1, it is estimated that school climate decreased by -0.0887 (95% CI [-0.1370, -0.0404]), $p = .001$. When missing data was present during COVID year 2, it is estimated that school climate increased by 0.1006, (95% CI [0.0382, 0.1629]), $p = .001$. There was an effect size of 0.7034 for the interaction between missing data and COVID year 1 and 0.7978 for the interaction between missing data and COVID year 2. ICC values indicate that 54.75% of the variance in the model is explained by variations between schools. Additionally, there is 0.0064 variance between schools on overall student perception of school climate, while schools vary in slope by 0.0020 during COVID year 1 and 0.0030 during COVID year 2. Residual variance indicates that there is a .0053 unexplained variance within schools. Figure 1 visualizes the observed longitudinal trajectory, and Figure 2 provides a closer look at the change in school climate by changing the y – axis to values where school climate was observed. Figure 3 visualizes the observed longitudinal trajectory with imputed data when data was present for both the 2019 – 2020 and 2020 – 2021 school year and when data was imputed during the 2020 – 2021 school year.

TFI Models

Unconditional Model

An unconditional model (Model 1t, Appendix J) was conducted to investigate the grand mean of school climate across the years. Through comparison of model fit statistics, the unconditional growth model without random effects (Model 2t) had better model fit (AIC = -891.91, BIC = -866.29, LogLik = 451.95, deviance = -903.91), compared to the unconditional model. A pooled likelihood ratio test supported these comparisons, $F(3, 5791.96) = 10.79$, $p < .001$, RIV = .29. Model 3t added random effects to both COVID year 1 and COVID year 2. Random effects were tested in five randomly selected models, all of which indicated that the inclusion of random effects at COVID year 1 and COVID year 2 improved model fit, (Model 1: $\chi 2(6) = 158.26$, $p < .001$; Model 2: $\chi 2(6) = 165.46$, $p < .001$; Model 3: $\chi 2(6) = 141.41$, $p < .001$; Model 4: $\chi 2(6) = 170.63$, $p < .001$; Model 5: $\chi 2(6) = 158.67$, $p < .001$). The unconditional model with random effects was used as a base model for conditional models.

Conditional Model

The main effect of meeting PBIS fidelity of implementation was assessed through a conditional model with a dichotomous variable of meeting PBIS fidelity of implementation as the only predictor (Model 4t). Comparison of fit indices found that the model with the main effect of meeting PBIS implementation had slightly worse AIC and BIC statistics compared to the unconditional growth model with random effects. A pooled likelihood ratio test did not find a significantly better model fit, $F(1, 6577.53) = 0.031$, $p = .859$, RIV = .13. After the main effect of PBIS implementation was assessed, Model 5 included interaction effects for PBIS implementation and each piecewise covariate.

As shown in Table 11 (Appendix I), Model 5t estimates revealed that all piecewise time covariates and the main and interaction effects of the TFI were not significant predictors of school level student perception of school climate. Model 4t was interpreted model fit statistics indicated better model fit, although a pooled likelihood ratio test did not find a significantly better model fit, $F(3, 3706.58) = 0.81$, $p = .489$, RIV = .39. Model 4t estimates indicate school climate scores during the intercept (2018 – 2019 school year) was 3.1285 (95% CI [3.0782, 3.1788]), $p = .001$. Estimates of the piecewise time covariates indicate that there was not a statistically significant change in school climate during the pre-COVID school years, $p = .315$. After the onset of the pandemic, there was a statistically significant increase in school climate scores 0.0512 (95% CI [0.0258, 0.0766]), $p = .001$ between the 2019 – 2020 and 2021 - 2022 school years, followed by a statistically significant decrease in school climate of -0.0494 (95% CI [-0.0738, -0.0250]), $p = .001$, between the 2020 – 2021 and 2021 – 2022 school years. There was an effect size of 0.3443 for COVID year 1 and an effect size of 0.3322 for COVID year 2. Meeting PBIS fidelity of implementation was not a significant predictor, $p = .859$. ICC values indicate that 59.91% of variance in the model was explained between differences in schools. Random effects indicate that .0077 variance was found between the grand mean of school climate, while .0053 variance occurred during COVID year 1 and .0040 during COVID year 2. There was also .0051 unexplained variance in the model.

Robustness Checks and Sensitivity Analysis

Models were assessed for modeling assumptions such as linearity, homogeneity of variances, presence of outliers, collinearity, and normality of residuals. The final full sample model violated assumptions of homoscedasticity and normality. When using diagnostic assumption tests through the *performance* package, five randomly selected models all violated homoscedasticity (Model 1, $p < .001$; Model 2, $p < .001$; Model 3, $p < .001$; Model 4, $p < .001$; Model 5, $p < .001$), and normality of residuals (Model 1, $p < .001$; Model 2, $p = .004$; Model 3, $p < .001$; Model 4, $p = .022$; Model 5, $p = .044$).

Robustness checks (i.e., models to investigate accuracy of estimates) and sensitivity analysis (i.e., models to investigate estimates if variables were operationalized differently) were conducted for the final full sample model. Differences in significant predictors between models that included robustness checks and sensitivity analysis are summarized in Table 12 (Appendix K). Due to model assumption violations, a model with a log-transformed dependent variable was conducted (Appendix R, tables R1 and R2). There were significant differences between the log-transformed model and the final model. The log-transformed model found the school-level percent of minoritized students, $p = .038$ to be significant. This model estimated that having a school racial composition with one percent higher proportion of minoritized students was associated with a 0.0195 increase in log-transformed school climate. The log-transformed model was assessed for model assumptions. Heteroskedasticity and normality of variances was not corrected in log-transformed models.

As the log-transformed model did not meet model assumptions, a second robustness model was conducted with a log-transformed dependent variable, and a trimmed dataset within 2.5 standard deviations (Appendix S). There were no significant differences between the z-transformed and trimmed model and the final model. Log-transformed and trimmed models continued to violate assumptions of homoscedasticity and normality of residuals.

Assumptions were evaluated for the TFI subsample model. Model 4t (Table 11) violated homoscedasticity in five randomly selected models (Model 1, $p < .001$; Model 2, $p < .001$; Model 3, $p < .001$; Model 4, $p < .001$; Model 5, $p < .001$) and normality in four of five randomly selected models (Model 1, $p = .084$; Model 2, $p = .010$; Model 3, $p < .001$; Model 4, $p = .002$; Model 5, $p < .001$). Log-transformed (Appendix T, tables T1 and T2) and log-transformed and trimmed at 2.5 standard deviations (Appendix U, tables U1 and U2) robustness checks were conducted for the TFI subsample model. The log-transformed and log-transformed and trimmed models did not correct heteroscedasticity or normality of residuals. Meeting PBIS fidelity of implementation remained non-significant across the final interpreted model $p = .859$, the log-transformed model $p = .817$, and the log-transformed and trimmed model $p = .943$.

As advocated by researchers (Grund et al., 2016) comparing imputed models to non-imputed models is necessary to evaluate bias within the models. The final model without imputation (Appendix V, tables V1 and V2), produced similar estimates for the intercept, the change between the 2019 – 2020 and 2020 – 2021 school years (COVID year 1), and between the 2021 – 2022 school years (COVID Year 2). The model without imputation produced higher estimates for the proportion of students receiving free or reduced lunch in a school (imputed model: $\beta = -0.0018$, model without imputation: $\beta = -0.1976$). Additionally, the model without imputation found that one percent higher school-level proportion of students coming from a racial or ethnically minoritized background (dichotomous racial and ethnic variable) was significantly associated to a 0.0775 higher average school climate, $p = .014$. Additionally, the model without imputation estimated that schools in a suburban locale were associated with

0.0432 higher school average perception of school climate, $p = .016$. The model without imputation demonstrated low multicollinearity and had minimal outliers but violated assumptions of heteroskedasticity and normality of residuals.

Three sensitivity analysis were conducted with the final full sample model. This approach was utilized to account for potential differences between model estimates when investigating data anomalies or approaching the model through differing variable operationalizations (Dedrick et al., 2009). The final sample model did not disaggregate school-level racial composition, and instead included a dichotomous variable for the school-level effect of the percent of students identified as racially and ethnically minoritized populations, as recorded by NCES school-wide demographics. Prior research has found that the aggregation of racial data as a dichotomous variable can lead to inaccurate results and incorrect conclusions (Allen et al., 2008; Teranishi et al., 2020). A sensitivity analysis was conducted disaggregating this dichotomous variable to investigate the school-level effect of NCES racial composition categories, such as the percent of students from American Indian/Native American, Asian / Pacific Islander, Black / African American, Latine, Native Hawaiian / Other Pacific Islander, or multiracial identified students within a school. The final model using disaggregated racial data (Appendix W, Model 5), estimated that the school-level main effects of disaggregated racial composition was not significant for the school-level proportion of NCES identified American Indian/Native American students, $p = .650$, Asian / Pacific Islander students, $p = .498$, Black / African American students $p = .300$, Latine students, $p = .085$, Native Hawaiian / Other Pacific Islander students $p = .536$, or multiracial identified students $p = .065$. These results estimate that the school-level composition of disaggregated NCES racial demographics does not relate to school average student perception of school climate. It should be noted that school-level disaggregated racial and ethnic data does not represent individual student experiences and is more of a reflection of school composition. Lastly, the estimates for many of the disaggregated racial demographic categories had the highest standard error in the model, ranging from 0.0360 to 0.9185, indicating that these estimates may be less accurate.

Another analysis was conducted with the inclusion of schools that had more than one survey completed at their school (Appendix X, Tables 1X and 2X) and one model with an added weight of school total enrollment. There were 14 schools added to the model with more than one survey completed during any of the study years. All 14 schools had inconsistent survey completion across the years. For example, one school had 287 surveys completed during the 2018 – 2019 school year and 8 surveys completed during the 2019 – 2020 school year. One school with a total enrollment of 92 students and was eliminated from the full sample model as 16 (17.4%) students completed school climate surveys during the 2021 – 2022 school year. All other schools had a total enrollment between 135 – 818 students. The average of total enrollment for all 14 schools added to the model was 388.64, with an average school composition of 51.91% male students, 48.52% of students from a marginalized background, and 71.62% of students receiving free or reduced lunch. Of the 14 added schools, 5 schools were from a rural locale, 1 school was from a town locale, 4 schools were from a suburban area, and 4 schools were from an urban area.

Compared to the final full sample model, the model including schools with over one survey (Appendix X, Table X2) revealed differences in the significance of being in a suburban setting. The final model including schools with over one survey completed found being in a suburban area significant $p = .002$. Specifically, being in a suburban locale was estimated with a 0.0561 higher school-level average perception of school climate. The final model with weights of total enrollment (Appendix Y, Table Y2) did not have significance differences from the final sample model.

Two sensitivity analyses were also conducted for the TFI subsample, one including school with more than one survey (Appendix Z, Tables Z1 and Z2) and with an added weight of total school enrollment (Appendix AA, Tables AA1 and AA2). There were no significance differences between the main effect model including schools with over one survey completed and the final main effect model (Model 4t, Table 11). Meeting PBIS fidelity of implementation was not a significant predictor in the main effects model, $p = .859$, or in the sensitivity main effects analysis, $p = .931$ (Model 4t, Table L2). Similarly, the model with a weight of school total enrollment did not find meeting PBIS fidelity of implementation significant $p = .899$.

CHAPTER IV

DISCUSSION

The current study used data from 195 elementary schools to investigate average ratings of student perception of school climate one year before the pandemic, and how school climate changed during year one and year two of the COVID-19 pandemic (research question one). This study also investigated how change in school climate relates to school level characteristics, such as school total enrollment, school racial and gender composition, the percent of students receiving free or reduced lunch, and school locale (research question two). School-level gender identity, school-level racial and ethnic identity, and school-level number of students receiving free or reduced lunch was used to investigate school-characteristics and effects. Additionally, the present study also investigated how change in school climate perception was associated with PBIS fidelity of implementation (research question three).

Level and Change in Perceived School Climate

Student perceptions of school climate remained relatively stable the year before, and two years after onset of the COVID – 19 pandemic, with an estimate of 3.13 for the schoolwide average student perception of school climate during the 2018 – 2019 school year. Although schoolwide average scores on the Georgia Elementary School Climate survey remained stable, there was a statistically significant but modest increase in student perception of school climate between the 2019 – 2020 and 2020 – 2021 school years (COVID year 1). Alongside this small increase in school climate scores during COVID year 1, there was a statistically significant decrease between the 2020 – 2021 and the 2021 – 2022 school years. Therefore, any increase in school climate during COVID year 1 disappeared during COVID year 2.

Contrary to our initial hypothesis for research question one, student perception of school climate did not decrease substantially during the onset of the pandemic. Instead, schoolwide averages align with prior research using the Georgia Elementary School Climate Survey. Prior studies found an average of 3.22 during the 2013 – 2014 school year, and an average of 3.12 during the 2017 – 2018 school year (La Salle et al., 2016; La Salle, 2020). Although there was a statistically significant change during COVID year 1 and 2, prior researchers have noted that these small changes in school climate may not be clinically significant (Elrod et al., 2022). Schoolwide averages may be less sensitive to changes in a student's perception of school climate compared to item-level responses, as the California Elementary School Climate Report Card saw larger changes in item-level data before and throughout the onset of the COVID-19 pandemic (California Survey System, 2022). Additionally, it may be that student perception of school climate was not impacted throughout the COVID-19 pandemic as schools implementing PBIS were able to continue to engage in supportive school and classwide educational practices regardless of modality of instruction.

It is speculated that changes in school practices may have reduced negative experiences and increased positive experiences within the educational setting, thus contributing to the possible increase in school average student perception of school climate during the 2020-2021 school year. Additionally, school disciplinary practices may have also resulted in changes in student perceptions. For instance, schools often use and report ODRs to monitor the number of formal student corrections. Research has found that students with higher disciplinary incidences have lower perceptions of school climate (Fefer & Gordon, 2018; Huang & Anyon, 2020). Welsh (2022) found that the number of ODRs decreased during the 2020 – 2021 school year. This reduction of ODRs may be associated to an increase in school average student perception of school climate, especially for students with higher numbers of ODRs. Alongside discipline, another common negative schooling experience is the presence of in-person bullying and cyber bullying. By analyzing the number of internet searches, Bacher-Hicks and colleageus (2022) found that there was a 30% reduction in bullying, school bullying, and cyber bulling during the 2020 – 2021 school year during school closures. Research has identified the negative association between experiences of bullying and victimization and school climate (Aldridge et al., 2018). The reduction of bullying experiences during the 2020 – 2021 school year may have contributed to the rise in climate scores that same year as students were engaged in remote learning and no longer present in the contexts where bullying may have occurred.

Along with the reduction of negative school experiences, COVID-19 prevention practices may have also contributed to the promotion of positive school experiences. Larivière-Bastien and colleagues (2022) found that over two-thirds of students desired to be back in in-person instruction, and one half of students missed school the most during the pandemic. Once students returned to schools, this desire to engage in traditional educational practices and the return to traditional instruction, may have influenced student perception of school climate. Physical distancing between students may have reduced class size, as some states required three feet between students' desks (Michigan Department of Health and Human Services, 2021) giving students smaller class sizes and more opportunities to engage with teachers and their peers in a small group setting. These smaller classes may have promoted an educational context characterized by more student-teacher interactions (Blatchford et al., 2011). Higher social support from teachers has been associated to feelings of safety (Coyle et al., 2022), which potentially changed the quality of student-teacher relationships during the 2020 – 2021 school year and contributed to more positive school average student perception of school climate.

Factors Associated with Perceived School Climate

The school-level percent of minoritized students was not associated with schoolwide average perception of school climate. This non-significant finding represents school-level characteristics. Surprisingly, school-level composition of minoritized students did not align with prior research, as studies have found that a student's racial and ethnic identity is related to perception of school climate (Fan et al., 2011; Koth et al., 2008; La Salle et al., 2016; Parris et al., 2018). Students coming from minoritized identities have rated school climate more negatively compared to White peers (Fan et al., 2011). Study findings may not have aligned with prior literature due to the use of school-level racial and ethnic summaries, which do not accurately represent the lived experiences of individual students. Additionally, school-level summaries are not sensitive to detect meaningful differences between racial/ethnic student identities, and a dichotomous racial variable may limit our ability to detect school-characteristic differences.

Research has advocated for the use of disaggregated racial and ethnic data, as dichotomous racial variables may produce biased or inaccurate estimates (Allen et al., 2008; Teranishi et al., 2020). Prior research has also outlined the importance of disaggregated racial and ethnic data, as studies have identified differences in racial and ethnic subgroup perception of school climate, given that school experiences have been shown to vary due to an individuals' perspective and culture (Fan et al., 2011; Parris et al., 2018). A sensitivity analysis using disaggregated NCES school-level racial and ethnic data including the school-level percent of students from American Indian/Native American, Asian / Pacific Islander, Black / African American, Latine, Native Hawaiian / Other Pacific Islander, or multiracial identified students was conducted. This model estimated no significant main or interaction effects of school-level racial composition, further highlighting that school-level summaries may not representative of individual student experiences, and that these summaries may not be sensitive to the unique and important perspectives of students from a minoritized background.

Study findings indicated the school-level percent of students receiving free or reduced lunch within in a school was negatively related to school average student perception of school climate. As described above, school-level percent of students receiving free or reduced lunch only describes school characteristics, not the experiences of students. When holding other variables constant, having one standard deviation higher of students receiving free or reduced lunch enrolled at school was associated with a slightly lower average school climate scores. This finding is consistent with our hypothesis and support current literature, as studies have found a negative association of school SES on school climate (Ruiz et al., 2018; Stevenson, 2006). Although limitations regarding the use of school-level percent of students receiving free or reduced lunch are discussed below, these findings outline the importance of supporting schools serving a higher proportion of students receiving free and reduced lunch, as advocated for by the U.S. Department of Education (2021).

School total enrollment was also not associated with schoolwide student perception of school climate. This finding also does not support prior research, as Koth and colleagues (2008) found that school total enrollment was negatively associated to student perception of school climate. While it was hypothesized that school total enrollment would be negatively related to school climate, it may be that school total enrollment was not related due to COVID-19 prevention strategies (such as cohorting of students, or online instruction), or a decrease in student attendance (Carminucci et al., 2021).

PBIS Fidelity of Implementation

Contrary to the hypothesis, results show that there was not a significant relation between meeting PBIS fidelity of implementation during the 2018 – 2019 school year and schoolwide perception of school climate before and during the COVID-19 pandemic. It was hypothesized that schools with higher PBIS fidelity of implementation would have higher schoolwide perception of school climate throughout the COVID-19 pandemic. However, these findings did not support our hypothesis and do not align with prior research (Bradshaw et al., 2008b; Hauchens et al., 2017), as the implementation of PBIS has been linked to increases in student ratings of school climate. Prior research has outlined the relationship of longitudinal implementation of PBIS and its relationship to school climate over multiple years of adequate fidelity of implementation (Elrod et al., 2022). Given that a pandemic may have interrupted PBIS fidelity of implementation, this positive association may not have been identified, as changes in PBIS fidelity of implementation may have occurred during the transitions to different modalities of instruction. Additionally, although PBIS has been advocated for within remote instruction settings (Speight & Kucharczyk, 2021), research has yet to investigate the relation between PBIS implementation and school climate in virtual settings.

Missing Data

Across study questions, missing data, or a lapse in administration of school climate surveys, was a major theme throughout this study. Demographic comparisons of patterns of missingness found that schools with the administration of school climate surveys each year except during the 2020 – 2021 school year (COVID year 1), had the largest student enrollment, served the highest proportion of minoritized students, and were primarily located in suburban areas. Although data may be missing for a variety of reasons, this finding highlights demographic information of schools that may have had obstructions of school assessment practices.

This study also investigated differences in school climate by pattern of missingness. Schools with a lapse of administration during the 2019 – 2020 and 2021 – 2022 school years, and schools with a lapse of administration during the 2019 – 2020 and 2020 – 2021 school years had statistically significant lower schoolwide student perception of school climate ratings compared to school with complete data. Alongside patterns of missingness, there were statistically significant differences when schools administered school climate surveys compared to when there was a lapse in the administration of school climate surveys for each year. Specifically, schools administering the school climate survey during the 2019 – 2020 school year had statistically significantly higher school climate during the 2018 – 2019, 2020 – 2021 and 2021 – 2022 school years compared to schools that had a lapse in school climate survey administration during the 2019 – 2020 school year. Additionally, those with present data during the 2020 – 2021 school year had slightly higher school climate scores in the 2021 – 2022 school year. These findings outline the importance of administering school climate surveys, and how a lapse in school climate administration may be related to a lower perception of school climate in proximal years.

Lastly, multilevel modeling estimated that the presence of imputed data at COVID year 1 was associated with a small, yet statistically significant decrease in school climate and a small, yet statistically significant increase during COVID year 2. Similar to previous findings, these results outline that a lapse in school survey administration may be related to a decrease in school climate, such that data was not available to account for student perceptions. Although imputed data is an estimate of what schoolwide school climate scores may be, these results continue to support the importance of yearly assessments of school climate, and how a lapse in school climate administration may be associated with an appearance of worsening school climate scores that may or may not be truly reflective of student experiences.

Limitations

This study is not without its limitations. Limitations of this study include the sample, inaccuracies in demographic, school climate, and PBIS fidelity of implementation data, and missing data across the years. With these limitations in mind, it is suggested that these results are only generalized to schools that have been implementing PBIS since or before the 2018 – 2019 school year and collected school climate data once before and once after the onset of the COVID-19 pandemic.

Sample Composition

As stated above, there are limitations with the sample. To start, the sample in this study is not representative of U.S public elementary schools. The schools in this sample were implementing PBIS throughout the years included in this study, starting before or during the 2018 – 2019 school year. The implementation of PBIS may have met adequate fidelity of implementation throughout the four years included in this study. Prior research has found that benefits of PBIS may take place after three years of implementation (Kim et al., 2018), and that those with added prior years of PBIS implementation had higher gains of school climate each year (Elrod et al., 2022).

Alongside consecutive implementation of PBIS, only a small proportion of those schools monitored school climate using the survey in this study. Within these schools, this sample consisted of a subset of schools that use the Georgia Elementary School Climate survey and PBISApps to store data. This subset of schools that annually monitors school climate as a part of their school leadership practices may have a higher school-level perception of school climate compared to those who do not monitor school climate yearly given their school culture surrounding PBIS implementation.

To be included in the study, schools in this sample also had to monitor school climate data before and after the onset of the COVID-19 pandemic. This may create bias within the sample, as schools that collected school climate data before the pandemic and were unable to assess school climate after the onset of the pandemic may have experienced different trajectories of school climate compared to the included sample. Taken together the limitations of the included sample, findings from this study may only be generalizable to schools implementing PBIS that assessed school climate schoolwide.

Accuracy of Data

The accuracy of demographic, school climate and PBIS fidelity of implementation data is also a limitation. This study used NCES demographic data during the 2018 – 2019 school year. Throughout the pandemic, school systems had a change in enrollment (Dee & Murphy, 2021), and enrollment data prior to the pandemic may not capture changes in the student population. Included in potential shifting of school-level demographic data may be an overall change in the number of total students, school composition of the number of students from racially marginalized groups, and the school composition of the number of students receiving free or reduced lunch. Therefore, schoolwide demographic data from the 2018 – 2019 school year may not accurately schoolwide demographic data throughout the 2019 – 2020, 2020 – 2021 and 2021 – 2022 school years.

Along with potential inaccuracies of NCES racial demographic data, this study did not investigate the level or change in student perception of school climate for individual subgroups of Asian or Pacific Islander, Black or African American, Latine, Native American, Native Hawaiian or Other Pacific Islander, or multiracial identity students. Instead, this study investigated how the school-level percent of students coming from a minoritized background within a school was associated with school average student perception of school climate. This operationalization only consists of school-level racial compositions, not student racial or ethnic identity, and considered potential inaccuracies within school-level summary data.

In combination with potential inaccuracies of demographic data, the gender and racial demographic information represents school-level summaries, which may not be reflective of individual student count, as these counts are not representative of individual student experiences, and do not incorporate a diverse range of people's racial or ethnic identity. Current research advocates for the avoidance of government racial categorization, as siloing individuals to few racial or ethnic identities contributes to under identifying inequities and under serving students (Yeung & Mun, 2022). Nguyen and colleageus (2019) found that by disaggregating Asian American and Pacific Islander into 23 racial and ethnic subgroups, there were statistically significant differences in risk ratio, indicating inequities in discipline for Cambodian identifying students.

Alongside racial and ethnic identity, research has questioned the accuracy and utility of free or reduced lunch data. Domina and colleagues (2018) found that school-level aggregated percent of free or reduced lunch had high variability regarding the composition of student family income. The authors found that schools with similar total percent of students receiving free or reduced lunch had an almost 10% difference in students from families that were classified as "currently in poverty" by the Internal Revenue Service. These findings, and the authors, suggest that the percent of students receiving free or reduced lunch is not an accurate representation of household income, supporting that school-level summaries do not reflect individual student experiences.

Although it is assumed that the students that completed the school climate survey were representative of the gender and racial demographics within a school, this assumption may be inaccurate. It is possible that students who completed school climate surveys throughout the pandemic may have had higher perception of school climate than those who did not. Throughout the pandemic, there was an overall decrease in attendance (Carminucci et al., 2021), which may have resulted in students being accidently excluded from school climate survey administration if they were absent on assessment days. If schools administered the school climate survey virtually, students without internet access at home may have been excluded from the schoolwide sample.

There may be inaccuracies in schoolwide student perception of school climate data. The school-year school average operationalization includes schools that administered the survey one or more times; however this study was unable to examine differences between schools with one survey administration, and schools with more than one survey administration in a year. Schools with multiple administrations may have a different school average student perception of school climate than those that have one survey administration. Previous research has not yet validated this scale with remote or hybrid instructional practices. Students engaged with a variety of modality of instruction practices throughout the pandemic and without prior research of differences in school climate data by modality of instruction, it is unknown if variability seen throughout the pandemic is due to changes in responding to in-person context specific questions (i.e., “I feel safe at school”). The modality of instruction for each school is unknown, and this study was unable to investigate or control for differences in online, hybrid or in-person instruction.

PBIS fidelity of implementation data during the 2018 – 2019 school year may also not provide an accurate representation of PBIS fidelity of implementation throughout the pandemic. First, it is unknown how PBIS fidelity of implementation changed across years, as schools meeting adequate implementation during the 2018 – 2019 school year may have been unable to maintain adequate implementation during the pandemic. Additionally, adequate PBIS implementation during only one school year does not account for prior implementation of PBIS. Elrod and colleagues (2022) found that those without prior PBIS implementation made continuous and large growth on measures of PBIS fidelity of implementation (Elrod et al., 2022), which may indicate that more schools in the sample met PBIS fidelity of implementation over time. On the contrary, these studies did not investigate how a nationwide pandemic influences PBIS fidelity of implementation. Statewide reports indicate the PBIS fidelity of implementation fell during the COVID-19 pandemic; however, there was a 20 to 30% decrease in the number of fidelity assessments completed (Florida PBIS, 2021; Missouri School Wide Positive Behavior Support, 2021). Therefore, the accuracy of 2018 – 2019 PBIS fidelity of implementation is a limitation, as implementation may have changed throughout the following years.

Implications for Policy and Practice

While interpreting the results of this study with limitations in mind, these results provide implications for future education policy and research. Education policy should continue to advocate for the yearly collection of schoolwide student perception of school climate data. Educational policies may be helpful in supporting schoolwide data collection efforts aimed at addressing school climate and reduce implementation barriers which in turn may assist with missing data. Policies may also benefit support practices that bolster school climate within higher risk schools, including schools that serve a higher proportion of students receiving free or reduced lunch.

As stated, education policy should continue to support the yearly collection of school climate data. Prior research has outlined the importance of using research validated scales that measure school climate through subdomains of safety, relationship, teaching and learning, and the educational environment (Thapa et al., 2013). Results from this study indicate that schools with complete data had higher student perception of school climate compared to schools with certain patterns of missing data. Additionally, schools that collected school climate data during the 2019 – 2020, 2020 – 2021, and 2021 - 2022 school years had statistically higher schoolwide student perception of school climate in one or more adjacent school years compared to schools with missing data. Specifically, schools with data present during the 2019 – 2020 school year had higher student perception of school climate during the 2018 – 2019, 2020 – 2021, and 2021 – 2022 school years. These results add to the literature base regarding the importance of assessing school climate, as schools implementing PBIS with repeated measures of school climate found a slight increase (.15) in school climate each year (Elrod et al., 2022).

The most common pattern for a lapse in school climate survey administration was the school year after the onset of the pandemic. As discussed previously, the absence of school climate survey administration may be related to barriers for typical systems functioning. The presence and concern of a lapse in school climate survey administration was a main theme throughout this study and should be explicitly addressed through policies and procedures that can support school leadership and equity teams in building capacity and sustainable practices for school climate assessment. In this sample, schools that had missing data directly after the onset of the pandemic were suburban schools with larger school enrollment that served a higher proportion of minoritized students. Patterns of missing data may differ in other samples, but these patterns may need to be further explored within districts. Schools with missing data may benefit from additional supports to maintain school climate data through consultation and aid in data collection, storage and data management and interpretation. Researchers have advocated for the use of school climate data to monitor the school context and inform decisions for school policies to improve school climate through tiered systems of support (La Salle, 2018). Policies can encourage mandated protocols and support the collection and interpretation of school climate assessment data, which may be beneficial when experiencing transitions within the school setting.

Prior research has identified the negative relation between the proportion of students receiving free or reduced lunch and student perception of school climate (Ruiz et al., 2018; Stevenson, 2006). This study supports prior research and expands this finding to schools that are implementing PBIS and assessed school climate before and during the pandemic. Although limitations are discussed regarding the accuracy of school-level percent of students receiving free or reduced lunch data, policy and practices should support schools serving a high percentage of students receiving free or reduced lunch by supporting in the collection of school climate data. By collecting school climate data, schools with a high composition of students receiving free or reduced lunch are able to monitor and make informed decisions regarding student perception of school climate. If data indicates that there is a need to target supports to improve student perception of school climate, schools may implement professional development for practices that have been associated with an improvement school climate, such as PBIS (Charlton et al., 2021). Implemented policies and practices could also support schools by mitigating circumstances that are related to a negative school climate, such as high faculty turnover (Koth et al., 2008).

Implications for Research

In addition to replication of current findings, future research should explore student-level and item-level data and investigate how state-wide COVID-19 prevention practices and modality of instruction relate to perception of school climate. To start, findings from this study need to be replicated across similar and different populations. This study investigated how school climate changed throughout the pandemic in a sample of schools implementing PBIS that assessed school climate with the Georgia Elementary School Climate Survey once before and once after the onset of the pandemic. Future research should investigate the trajectory of school climate in non-participating schools that did not implement PBIS, and schools that use a different outcome evaluation system and school climate assessment. Other validated school climate assessments (e.g., the Georgia Secondary School Climate Survey) consist of more than one factor, which could provide more a more in-depth investigation of the aspects of school climate that may have changed. Research in other populations may find similar or different results.

Along with replication with different samples that did not implement PBIS and used different school climate assessment systems, future research should investigate student-level data on the Georgia Elementary School Climate survey. As noted, this study used school-level averages of school climate and school-level demographic information, which may not exactly match the student demographics of those who completed school climate surveys. These school-level summaries do not reflect an individual's experience. Future research using student-level data with disaggregated racial and ethnic identities will provide a more accurate investigation of how student racial and ethnic identities are associated with perception of school climate and the trajectory of school climate throughout the pandemic. Along with disaggregated racial and ethnic data, other metrics of school or student socio-economic status may be more informative compared to NCES identified school-level proportion of students receiving free or reduced lunch. Future research should investigate student-level trajectories using more accurate methods to identify school-level socio-economic status. Research on item-level data may also provide unique information. An analysis of item level data may reveal that some individual survey items changed throughout the pandemic, while others remained constant. Patterns of changing items may be related to demographic information or school practices and may better inform future school practices.

Lastly, research has yet to investigate how COVID-19 practices and procedures are related to school climate. Future research should investigate the relationship between pandemic prevention practices (e.g., physical distancing, cohorting of students, and modality of instruction) and student perception of school climate. Additionally, research investigating modality of instruction and school climate may inform future assessment on best practices in assessing school climate for students in remote and hybrid educational settings. Preventative practices used during the pandemic may not only provide future guidance to educators about the relationship of these practices to school climate, but also increase use of practices that were beneficial to students and school settings that experienced declines in school climate perception and PBIS fidelity of implementation.

APPENDICIES

A. SCHOOL DEMOGRAPHIC INFORMATION

Table 1

School demographic information

Demographic Information	*M*	%	SD	Range
Total Enrollment (*N* = *195*)	444.96		150.08	110 – 829
Male Students		51.69	2.59	42.75 – 59.02
Minoritized Students		55.61	36.58	1.99 - 100
Receiving FRL		65.32	24.70	4.09 – 99.24
Locale				
Urban (*N* = *29*)		15		
Suburban (*N* = *110*)		56		
Town (*N* = *21*)		11		
Rural (*N* = *35*)		18		

Note. Male = school composition of male students. Minoritized = school composition of racially and ethnically minoritized students. FRL = school composition of students receiving free or reduced lunch

B. DESCRIPTIVE STATISTICS FOR SCHOOL CLIMATE AND FIDELITY OF IMPLEMENTATION

Table 2

Descriptive statistics for school climate and fidelity of implementation.

Variable	*N*	*M*	%	SD	Range
School Climate					
2018 - 2019	147	3.14		0.12	2.85 – 3.46
2019 - 2020	164	3.17		0.11	2.84 – 3.46
2020 - 2021	143	3.22		0.10	2.89 – 3.47
2021 - 2022	152	3.15		0.12	2.80 – 3.42
Survey Completion					
2018 - 2019	147		51.16	22.49	3.50 – 110.69
2019 - 2020	164		40.50	15.98	3.88 – 101.13
2020 - 2021	143		35.40	19.01	4.10 – 123.43
2021 - 2022	152		43.63	20.33	9.59 – 102.52
Tiered Fidelity Inventory					
2018 - 2019	132	85.40		13.45	40.00 – 100.00
Meeting Fidelity (≥ 70%)	117				
Not Meeting Fidelity (< 70%)	15				

C. PEARSON CORRELATIONS FOR SCHOOL CLIMATE AND DEMOGRAPHIC VARIABLES

Table 3

Pearson correlations for school climate and demographic variables.

Variable	1	2	3	4	5	6	7	8	9	10
1: SC 18 - 19										
2: SC 19 - 20	.71**									
3: SC 20 - 21	.47**	.51**								
4 :SC 21 - 22	.52**	.52**	.56**							
5: Total Enrollment	.12	.05	-.07	.03						
6: % Male	.01	-.01	.04	.01	-.12					
7: % Minoritized	-.14	-.17*	.01	-.08	.39**	-.05				
8: % FRL	-.39**	-.37**	-.18*	-.31**	.08	-.04	.71**			
9: Urban	-.12	-.25**	-.16	-.15	-.11	.08	.13	.11		
10: Suburban	.10	.09	.17*	.02	.41**	-.06	.46**	.15*	.48**	
11: Rural	-.02	.10	-.05	.09	-.37**	.01	-.61**	-.25**	-.27**	-.72**

Note. SC = School Climate, Male = school composition of male students. Minoritized = school composition of racially and ethnically minoritized students. FRL = school composition of students receiving free or reduced lunch, * = $p < .05$, ** = $p < .01$.

D. DIFFERENCES IN SCHOOL CLIMATE BY PATTERNS OF MISSINGNESS

Table 4

Differences in school climate by patterns of missingness

Missingness Pattern	N	%	2018 – 2019 *M* (*SD*)	2019 – 2020 *M* (*SD*)	2020 – 2021 *M* (*SD*)	2021 – 2022 *M* (*SD*)	Grand Mean *M* (*SE*)
1111	72	36.92	3.15 (.11)	3.16 (.11)	3.23 (.10)	3.17 (.13)	3.17 (0.01)
1101	37	18.97	3.17 (.11)	3.17 (.12)		3.14 (.11)	3.16 (0.01)
0111	26	13.33		3.18 (.09)	3.23 (.11)	3.16 (.08)	3.19 (0.01)
0110	19	9.74		3.18 (.09)	3.21 (.08)		3.19 (0.01)
1010	17	8.72	3.06 (.11)		3.16 (.07)		3.11 (0.02)[abc]
1001	12	6.15	3.10 (.13)			3.08 (.11)	3.09 (0.02)[abcd]
1110	7	3.59	3.21 (.14)	3.15 (.14)	3.25 (.11)		3.20 (0.02)
0101	3	1.54		3.15 (.10)		3.06 (.10)	3.11 (0.05)
1011	2	1.03	2.93 (.04)		3.18 (.03)	3.12 (.02)	3.08 (0.06)

Note. 1111 = present data during the 2018 – 2019, 2019 – 2020, 2020 – 2021, and 2021 – 2022 school years. 1101 = present data during the 2018 – 2019, 2019 – 2020, and 2021 – 2022 school years. 0111 = present data during the 2019 – 2020, 2020 – 2021, and 2021 – 2022 school years. 0110 = present data during the 2019 – 2020, and 2020 – 2021 school years. 1010 = present data during the 2018 – 2019 and 2020 – 2021 school years. 1001 = present data during the 2018 – 2019, and 2021 – 2022 school years. 1110 = present data during the 2018 – 2019, 2019 – 2020, and 2020 – 2021 school years. 0101 = present data during the 2019 – 2020, and 2021 – 2022 school years. 1011 = present data during the 2018 – 2019, 2020 – 2021, and 2021 – 2022 school years. [a] = significantly different from schools with present data (1111), [b] = significantly different from schools with 0111, [c] = significantly different from schools with 0110, [d] = significantly different from schools with 1110

E. DIFFERENCES IN DEMOGRAPHIC INFORMATION BY PATTERNS OF MISSINGNESS

Table 5

Differences in demographic information by patterns of missingness

Pattern of Missing	1111	1101	0111	0110	1010	1001	1110	0101	1011
Schools (*N*)	72	37	26	19	17	12	7	3	2
Enrollment	408.75	573.54[a]	458.00[b]	396.16[b]	423.18[b]	370.83[b]	399.57	536.67	315.50
M (SD)	(139.00)	(125.67)	(143.45)	(116.20)	(161.05)	(158.81)	(90.46)	(110.39)	(37.48)
% Male	51.80	51.06	52.59	52.05	51.35	51.92	49.34	52.25	53.75
M (SD)	(2.65)	(2.53)	(2.01)	(2.99)	(2.41)	(2.04)	(3.38)	(1.05)	(2.80)
% Minoritized	54.47	79.03[a]	54.73	33.92[b]	68.36	20.34[abd]	39.98	72.59	15.52
M (SD)	(35.07)	(29.36)	(37.86)	(31.33)	(32.75)	(20.03)	(18.43)	(41.75)	(8.24)
% FRL	71.87	67.56	56.50	49.37[a]	75.56[c]	50.38	62.96	71.20	56.39
M (SD)	(21.11)	(21.81)	(30.19)	(24.40)	(25.09)	(14.70)	(33.31)	(29.66)	(19.08)
Urban	.21	.00	.12	.16	.35[b]	.00	.00	.67[b]	.00
Suburban	.44	.95[a]	.62	.51[b]	.53	.25[b]	.71	.00[b]	.00
Rural	.35	.05[ae]	.27[f]	.48	.12[e]	.75	.29	.33	1.00

Note. Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, [a] = significantly different from complete data (1111), [b] = significantly different from 1101, [c] = significantly different from 0110, [d] = significantly different from 1010, [e] = significantly different from 1001. 1111 = present data during the 2018 – 2019, 2019 – 2020, 2020 – 2021, and 2021 – 2022 school years. 1101 = present data during the 2018 – 2019, 2019 – 2020, and 2021 – 2022 school years. 0111 = present data during the 2019 – 2020, 2020 – 2021, and 2021 – 2022 school years. 0110 = present data during the 2019 – 2020, and 2020 – 2021 school years. 1010 = present data during the 2018 – 2019 and 2020 – 2021 school years. 1001 = present data during the 2018 – 2019, and 2021 – 2022 school years. 1110 = present data during the 2018 – 2019, 2019 – 2020, and 2020 – 2021 school years. 0101 = present data during the 2019 – 2020, and 2021 – 2022 school years. 1011 = present data during the 2018 – 2019, 2020 – 2021, and 2021 – 2022 school years.

F. DIFFERENCES BY YEAR OF MISSING DATA

Table 6

Differences in school climate and demographic information by year of missing data

	2018 - 2019		2019 – 2020		2020 – 2021		2021 – 2022	
	Present	Missing	Present	Missing	Present	Missing	Present	Missing
Schools (*N*)	147	48	164	31	143	52	152	43
SC 2018 - 2019			3.16	3.07**	3.14	3.15	3.15	3.10
SC 2019 - 2020	3.16	3.18			3.17	3.16	3.17	3.17
SC 2020 - 2021	3.22	3.22	3.23	3.16**			3.23	3.20*
SC 2021 - 2022	3.15	3.15	3.16	3.09*	3.17	3.12*		
Enrollment	447.09	438.44	454.23	395.97	415.99	524.64**	455.59	407.40*
% Male	51.47	52.36*	51.69	51.72	51.83	51.33	51.80	51.33
% Minoritized	58.22	47.61	57.36	46.36	52.15	65.11*	57.64	48.42
% FRL	68.83	54.60**	65.46	64.57	65.87	63.81	66.28	61.93
Urban	.14	1.66	.14	.19	.19	.04**	.13	.21
Suburban	.57	.54	.60	.39*	.50	.73**	.57	.56
Rural	.29	.29	.26	.42	.31	.23	.30	.23

Note. SC = School Climate, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch,* = $p < .05$, ** = $p < .01$.

G. MULTILEVEL DESCRIPTIVE STATISTICS FOR SCHOOL CLIMATE

Table 7

Multilevel descriptive statistics for school climate

Variable	All schools	Schools with TFI
Number of schools	195	132
Average number of timepoints	3.11 (0.79)	3.35 (0.77)
Range of timepoints	2 - 4	2 - 4
Mean	3.17	3.15
Variance Within	0.007	0.007
Variance Between	0.007	0.006
ICC	.50	.46
Design Effect	2.04	2.08

H. UNCONDITIONAL MODEL PARAMETERS

Table 8

Unconditional model parameters

	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1659**	0.0070	3.1512**	0.0092	3.1512**	.0091
Pre-Covid	$\gamma 10$			0.0068	0.0097	0.0068	.0090
CY1	$\gamma 20$			0.0442**	0.0095	0.0442**	.0097
CY2	$\gamma 30$			-0.0500**	0.0100	-0.0500**	.0099
				Random effects			
Residual	σ^2	0.0073		0.0067		0.0054	
Sch Intercept	U_{0i}	0.0068		0.0070		0.0080	
Sch CY1	U_{1i}					0.0030	
Sch CY2	U_{2i}					0.0021	
				Model fit			
AIC		-1318.71		-1331.86		-1365.40	
BIC		-1304.73		-1303.91		-1314.15	
logLik		662.35		671.93		693.70	
Deviance		-1324.71		-1343.86		-1387.40	
ICC		.4855		.5129		.5950	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School. AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

I. CONDITIONAL MODEL PARAMETERS

Table 9

Conditional model parameters

Variable	Parameter	Model 4		Model 5		Final Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	γ00	3.1216**	0.0178	3.1259**	0.0231	3.1335**	0.0120
Pre-Covid	γ10	0.0064	0.0091	-0.0159	0.0247	0.0084	0.0090
Covid Year 1	γ20	0.0448**	0.0097	0.0706**	0.0240	0.0659**	0.0093
Covid Year 2	γ30	-0.0502**	0.0099	-0.0695**	0.0249	-0.0754**	0.0099
Enrollment	γ01	-0.0000	0.0001	0.0000	0.0001		
% Male	γ02	0.0007	0.0025	0.0015	0.0033		
% Minoritized	γ03	0.0007*	0.0003	0.0003	0.0004	0.0005^{+}	0.0003
% FRL	γ04	-0.0020**	0.0004	-0.0020**	0.0005	-0.0018**	0.0004
Suburban	γ05	0.0374^{+}	0.0192	0.0321	0.0265	0.0217	0.0150
Rural	γ06	0.0309	0.0232	0.0070	0.0307		
Missing Data	γ07	-0.0054	0.0118	0.0167	0.0207	0.0180	0.0162
Enrollment*PreC	γ11			-0.0000	0.0001		
% Male*PreC	γ12			-0.0021	0.0034		
% Minoritized *PreC	γ13			0.0004	0.0004		
% FRL*PreC	γ14			-0.0001	0.0005		
Suburban*PreC	γ15			0.0191	0.0281		
Rural*PreC	γ16			0.0483	0.0327		
Missing Data*PreC	γ17			-0.0038	0.0341		
Enrollment*CY1	γ21			-0.0001	0.0001		
% Male*CY1	γ22			0.0006	0.0034		
% Minoritized *CY1	γ23			0.0004	0.0005		
% FRL*CY1	γ24			0.0003	0.0006		
Suburban*CY1	γ25			-0.0019	0.0279		
Rural*CY1	γ26			-0.0161	0.0322		
Missing Data*CY1	γ27			-0.0816*	0.0319	-0.0887**	0.0246
Enrollment*CY2	γ31			0.0001	0.0001		
% Male*CY2	γ32			0.0015	0.0039		
% Minoritized *CY2	γ33			-0.0003	0.0005		
% FRL*CY2	γ34			-0.0003	0.0006		
Suburban*CY2	γ35			-0.0187	0.0285		
Rural*CY2	γ36			0.0145	0.0336		
Missing Data*CY2	γ37			0.1016**	0.0325	0.1006**	0.0317
		Random effects					
Residual	σ^2	0.0055		0.0051		0.0053	
Sch Intercept	U_{0i}	0.0061		0.0063		0.0064	
Sch CY1	U_{1i}	0.0028		0.0016		0.0020	
Sch CY2	U_{2i}	0.0020		0.0018		0.0021	
		Model fit					
AIC		-1388.07		-1405.77		-1414.76	
BIC		-1304.21		-1224.06		-1335.55	
logLik		712.04		741.88		724.38	
Deviance		-1424.07		-1483.77		-1448.76	
ICC		.5267		.5543		.5475	

Note. Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch,, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

J. UNCONDITIONAL MODEL PARAMETERS (TFI)

Table 10

Unconditional model parameters (TFI)

Variable	Parameter	Model 1t		Model 2t		Model 3t	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1535**	0.0084	3.1327**	.0103	3.1327**	0.0099
Pre-Covid	$\gamma 10$			0.0100	.0114	0.0100	0.0100
CY1	$\gamma 20$			0.0512**	.0126	0.0512**	0.0129
CY2	$\gamma 30$			-0.0469**	.0124	-0.0494**	0.0124
Random effects							
Residual	σ^2	0.0079		0.0072		0.0051	
Sch Intercept	U_{0i}	0.0066		0.0068		0.0077	
Sch CY1	U_{1i}					0.0053	
Sch CY2	U_{2i}					0.0040	
Model fit							
AIC		-857.30		-891.91		-897.08	
BIC		-844.49		-866.30		-850.12	
logLik		431.65		451.96		459.54	
Deviance		-863.30		-903.91		-919.08	
ICC		.4531		.4858		.5995	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

K. CONDITIONAL MODEL PARAMETERS (TFI)

Table 11
Conditional model parameters (TFI) with Multiple Imputation

Variable	Parameter	Model 4t		Model 5t	
		Estimate	*SE*	Estimate	*SE*
Intercept	γ00	3.1285**	0.0257	3.1343**	0.0292
Pre-Covid	γ10	0.0100	0.0100	-0.0142	0.0324
CY1	γ20	0.0512**	0.0129	0.0661^{+}	0.0390
CY2	γ30	-0.0494**	0.0124	-0.0137	0.0373
Meet TFI	γ01	0.0047	0.0267	-0.0018	0.0310
Meet TFI*PreC	γ11			0.0273	0.0337
Meet TFI*CY1	γ21			-0.0169	0.0407
Meet TFI*CY2	γ31			-0.0402	0.0390
Random effects					
Residual	σ^2	0.0051		0.0051	
Sch Intercept	U_{0i}	0.0077		0.0077	
Sch CY1	U_{1i}	0.0053		0.0054	
Sch CY2	U_{2i}	0.0040		0.0040	
Model Fit					
AIC		-895.24		-893.79	
BIC		-844.01		-829.75	
logLik		459.62		461.90	
Deviance		-919.24		-925.79	
ICC		.5991		.6024	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

L. SIGNIFICANT COVARIATES AND PREDICTORS BETWEEN FINAL MODELS

Table 1L

Significant covariates and predictors between models

	Final Model	Log - Transformed	Log - Transformed and Trimmed	Disaggregated School-Level Racial Composition	Weight of Total Enrollment	>1 Survey Completed	Model Without Imputation
Time							
CY1	**	**	**	**	**	**	**
CY2	**	**	**	**	**	**	**
Predictor							
% Minoritized	N	*	N	NA	N	N	*
% Racial Subgroups Within School	NA	NA	NA	N	NA	NA	NA
% FRL	**	**	**	**	**	**	**
Suburban	N	N	N	N	N	**	*
Interactions							
CY1 * Missing	**	N	N	**	**	**	NA
CY2 * Missing	**	N	N	**	**	**	NA

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, ** = $p < .01$, * = $p < .05$, N = $p > .05$

M. OBSERVED SCHOOL CLIMATE THROUGHOUT THE PANDEMIC

Figure 1
Observed School Climate Throughout the Pandemic

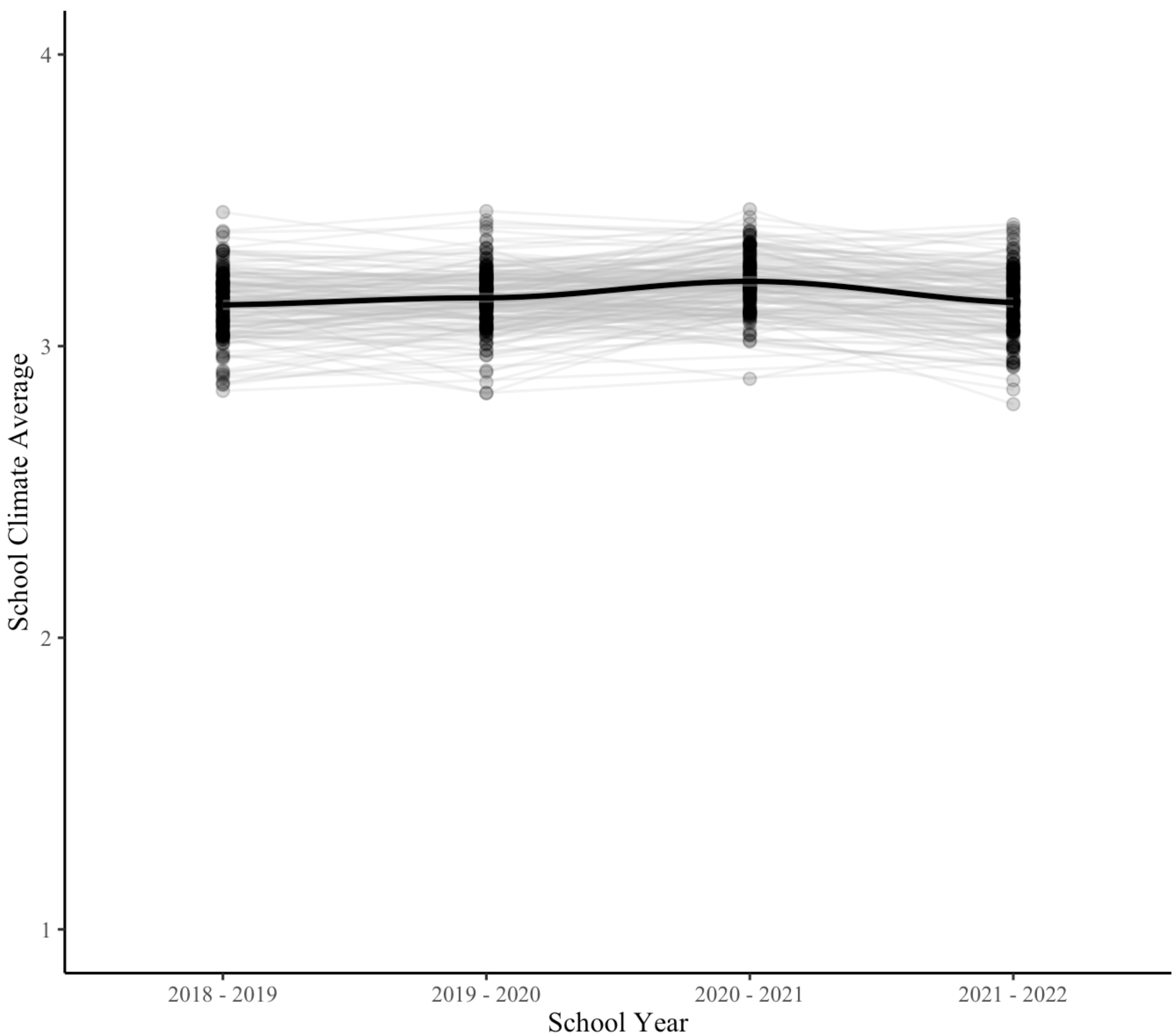
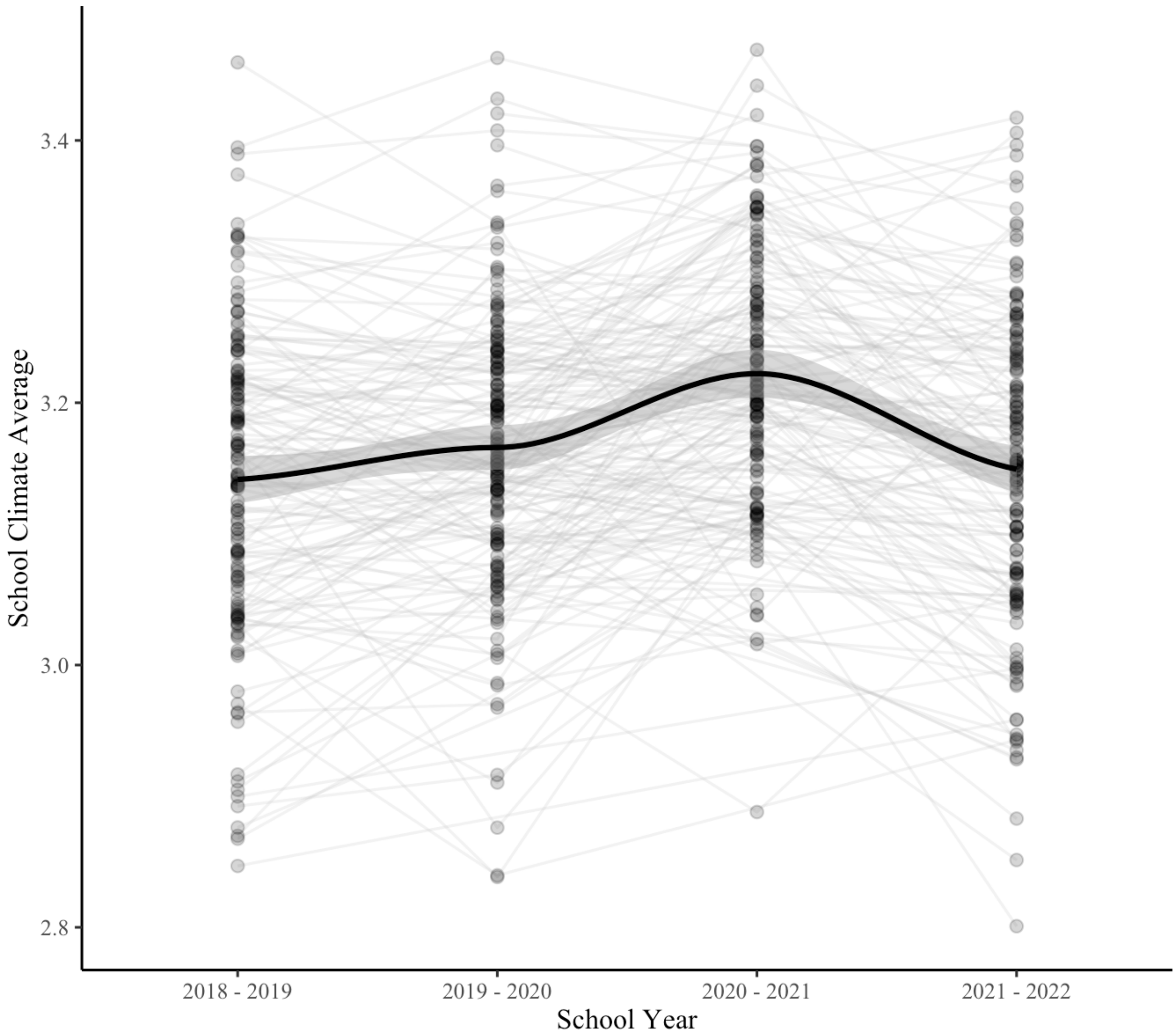


Figure 2

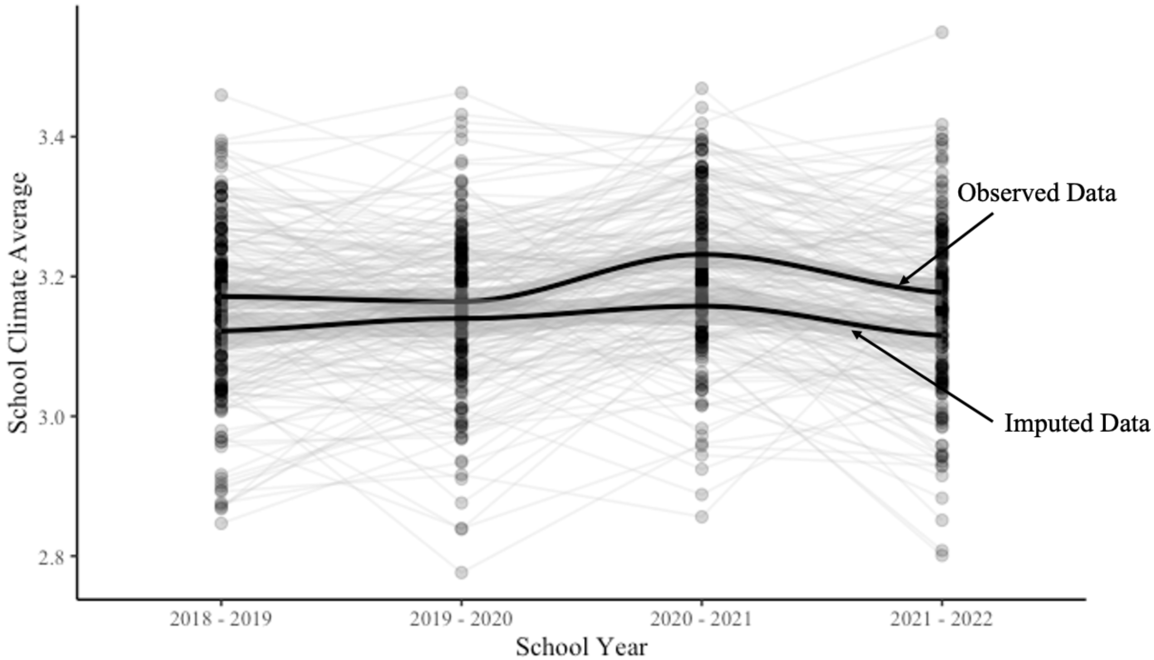
Zoom – In of Observed School Climate Throughout the Pandemic



O. OBSERVED AND IMPUTED TRAJECTORIES FOR MISSING DATA

Figure 3

Observed and Imputed Trajectories for Missing Data at COVID Year One



P. GEORGIA ELEMENTARY SCHOOL CLIMATE SURVEY

Scoring

1 – 4 Likert Scale: 1 – Never, 2 – Sometimes, 3 – Often, 4 – Always

Survey Questions:

1) I like school.
2) I feel like I do well in school.
3) My school wants me to do well.
4) My school has clear rules for behavior.
5) Teachers treat me with respect.
6) Good behavior is noticed at my school.
7) I get along with other students.
8) I feel safe at school.
9) Students treat each other well.
10) There is an adult at my school who will help me if I need it.
11) Students in my class behavior so teachers can teach.

Q. TIERED FIDELITY INVENTORY – TIER 1

Feature	Possible Data Sources	Scoring Criteria
Subscale: Teams		
1.1 Team Composition: Tier 1 team includes a Tier 1 systems coordinator, a school administrator, a family member, and individuals able to provide (a) applied behavioral expertise, (b) coaching expertise, (c) knowledge of student academic and behavior patterns, (d) knowledge about the operations of the school across grade levels and programs, and for high schools, (e) student representation.	School organizational chart Tier 1 team meeting minutes	0 = Tier 1 team does not exist or does not include coordinator, school administrator, or individuals with applied behavioral expertise 1 = Tier 1 team exists, but does not include all identified roles or attendance of these members is below 80% 2 = Tier 1 team exists with coordinator, administrator, and all identified roles represented, AND attendance of all roles is at or above 80%
1.2 Team Operating Procedures: Tier 1 team meets at least monthly and has (a) regular meeting format/agenda, (b) minutes, (c) defined meeting roles, and (d) a current action plan.	Tier 1 team meeting agendas and minutes Tier 1 meeting roles descriptions Tier 1 action plan	0 = Tier 1 team does not use regular meeting format/ agenda, minutes, defined roles, or a current action plan 1= Tier 1 team has at least 2 but not all 4 features 2 = Tier 1 team meets at least monthly and uses regular meeting format/agenda, minutes, defined roles, AND has a current action plan
Subscale: Implementation		
1.3 Behavioral Expectations: School has five or fewer positively stated behavioral expectations and examples by setting/location for student and staff behaviors (i.e., school teaching matrix) defined and in place.	TFI Walkthrough Tool Staff handbook Student handbook	0 = Behavioral expectations have not been identified, are not all positive, or are more than 5 in number 1 = Behavioral expectations identified but may not include a matrix or be posted 2 = Five or fewer behavioral expectations exist that are positive, posted, and identified for specific settings (i.e., matrix) AND at least 90% of staff can list at least 67% of the expectations
1.4 Teaching Expectations: Expected academic and social behaviors are taught directly to all students in classrooms and across other campus settings/locations.	TFI Walkthrough Tool Professional development calendar Lesson plans Informal walkthroughs	0 = Expected behaviors are not taught 1 = Expected behaviors are taught informally or inconsistently 2 = Formal system with written schedules is used to teach expected behaviors directly to students across classroom and campus settings AND at least 70% of students can list at least 67% of the expectations

1.5 Problem Behavior Definitions: School has clear definitions for behaviors that interfere with academic and social success and a clear policy/ procedure (e.g., flowchart) for addressing office-managed versus staff-managed problems.	Staff handbook Student handbook School policy Discipline flowchart	0 = No clear definitions exist, and procedures to manage problems are not clearly documented 1 = Definitions and procedures exist but are not clear and/or not organized by staff- versus office-managed problems 2 = Definitions and procedures for managing problems are clearly defined, documented, trained, and shared with families
1.6 Discipline Policies: School policies and procedures describe and emphasize proactive, instructive, and/ or restorative approaches to student behavior that are implemented consistently.	Discipline policy Student handbook Code of conduct Informal administrator interview	0 = Documents contain only reactive and punitive consequences 1 = Documentation includes and emphasizes proactive approaches 2 = Documentation includes and emphasizes proactive approaches AND administrator reports consistent use
1.7 Professional Development: A written process is used for orienting all faculty/staff on 4 core Tier 1 SWPBIS practices: (a) teaching school-wide expectations, (b) acknowledging appropriate behavior, (c) correcting errors, and (d) requesting assistance.	Professional development calendar Staff handbook	0 = No process for teaching staff is in place 1 = Process is informal/unwritten, not part of professional development calendar, and/or does not include all staff or all 4 core Tier 1 practices 2 = Formal process for teaching all staff all aspects of Tier 1 system, including all 4 core Tier 1 practices
1.8 Classroom Procedures: Tier 1 features (school-wide expectations, routines, acknowledgements, in-class continuum of consequences) are implemented within classrooms and consistent with school-wide systems.	Staff handbook Informal walkthroughs Progress monitoring Individual classroom data	0 = Classrooms are not implementing Tier 1 1 = Classrooms are informally implementing Tier 1 but no formal system exists 2 = Classrooms are formally implementing all core Tier 1 features, consistent with school-wide expectations
1.9 Feedback and Acknowledgement: A formal system (i.e., written set of procedures for specific behavior feedback that is [a] linked to school-wide expectations and [b] used across settings and within classrooms) is in place and used by at least 90% of a sample of staff and received by at least 50% of a sample of students.	TFI Walkthrough Tool Staff handbook	0 = No formal system for acknowledging students 1 = Formal system is in place and is used by at least 90% of staff OR received by at least 50% of students 2 = Formal system for acknowledging student behavior is used by at least 90% of staff AND received by at least 50% of students

1.10 Faculty Involvement: Faculty are shown school- wide data regularly and provide input on universal foundations (e.g., expectations, acknowledgements, definitions, consequences) at least every 12 months.	PBIS Self-Assessment Survey Informal surveys Staff meeting minutes Team meeting minutes	0 = Faculty are not shown data at least yearly and do not provide input 1 = Faculty have been shown data more than yearly OR have provided feedback on Tier 1 foundations within the past 12 months but not both 2 = Faculty are shown data at least 4 times per year AND have provided feedback on Tier 1 practices within the past 12 months
1.11 Student/Family/Community Involvement: Stakeholders (students, families, and community members) provide input on universal foundations (e.g., expectations, consequences, acknowledgements) at least every 12 months.	Surveys Voting results from parent/ family meeting Team meeting minutes	0 = No documentation (or no opportunities) for stakeholder feedback on Tier 1 foundations 1 = Documentation of input on Tier 1 foundations, but not within the past 12 months or input but not from all types of stakeholders 2 = Documentation exists that students, families, and community members have provided feedback on Tier 1 practices within the past 12 months
Subscale: Evaluation		
1.12 Discipline Data: Tier 1 team has instantaneous access to graphed reports summarizing discipline data organized by the frequency of problem behavior events by behavior, location, time of day, and by individual student.	School policy Team meeting minutes Student outcome data	0 = No centralized data system with ongoing decision making exists 1 = Data system exists but does not allow instantaneous access to full set of graphed reports 2 = Discipline data system exists that allows instantaneous access to graphs of frequency of problem behavior events by behavior, location, time of day, and student
1.13 Data-based Decision Making: Tier 1 team reviews and uses discipline data at least monthly for decision-making.	Data decision rules Staff professional development calendar Staff handbook Team meeting minutes	0 = No process/protocol exists, or data are reviewed but not used 1 = Data reviewed and used for decision-making, but less than monthly 2 = Team reviews discipline data and uses data for decision-making at least monthly. If data indicate a problem, an action plan is developed to enhance or modify Tier 1 supports
1.14 Fidelity Data: Tier 1 team reviews and uses SWPBIS fidelity (e.g., SET, BoQ, TIC, SAS, Tiered Fidelity Inventory) data at least annually	School policy Staff handbook School newsletters School website	0 = No Tier 1 SWPBIS fidelity data collected 1 = Tier 1 fidelity collected informally and/or less often than annually

		2 = Tier 1 fidelity data collected and used for decision making annually
1.15 Annual Evaluation: Tier 1 team documents fidelity and effectiveness of Tier 1 practices at least annually (including year- by-year comparisons) that are shared with stakeholders (staff, families, community, district) in a usable format.	Staff, student, and family surveys Tier 1 handbook Fidelity tools School policy Student outcomes District reports School newsletters	0 = No evaluation takes place, or evaluation occurs without data 1 = Evaluation conducted, but not annually, or outcomes are not used to shape the Tier 1 process and/ or not shared with stakeholders 2 = Evaluation conducted at least annually, and outcomes shared with stakeholders, with clear alterations in process based on evaluation

R. LOG-TRANSFORMED FULL SAMPLE MODEL

Table R1

Unconditional model parameters for log-transformed model

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	1.1518**	0.0026	1.1476**	0.0040	1.1476**	.0040
Pre-Covid	$\gamma 10$			0.0017	0.0047	0.0017	.0046
CY1	$\gamma 20$			0.0139**	0.0046	0.0139**	.0046
CY2	$\gamma 30$			-0.0159**	0.0048	-0.0159**	.0048
Random effects							
Residual	σ^2	0.0013		0.0012		0.0011	
Sch Intercept	U_{0i}	0.0007		0.0008		0.0009	
Sch CY1	U_{1i}					0.0004	
Sch CY2	U_{2i}					0.0005	
Model fit							
AIC		-2727.64		-2750.37		-2747.76	
BIC		-2713.66		-2722.42		-2696.50	
logLik		1366.82		1381.19		1384.88	
Deviance		-2733.64		-2762.37		-2769.76	
ICC		.3636		.380		.438	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School. AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intraclass Correlation

Table R2

Unconditional model parameters for log-transformed model

Variable	Parameter	Model 4		Model 5		Final Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	γ00	1.1392**	0.0070	1.1405**	0.0101	1.1484**	0.0036
Pre-Covid	γ10	0.0015	0.0045	-0.0043	0.0120	0.0013	0.0045
Covid Year 1	γ20	0.0142**	0.0046	0.0210*	0.0107	0.0144**	0.0046
Covid Year 2	γ30	-0.0160**	0.0048	-0.0225	0.0116	-0.0182**	0.0046
Enrollment	γ01	-0.0000	0.0000	0.0000	0.0000		
% Male	γ02	0.0001	0.0009	0.0004	0.0015		
% Minoritized	γ03	0.0219^{+}	0.0124	0.0101	0.0179	0.0206*	0.0092
% FRL	γ04	-0.0643**	0.0150	-0.0654**	0.0226	-0.0642**	0.0140
Suburban	γ05	0.0111	0.0074	0.0087	0.0117		
Rural	γ06	0.0086	0.0088	-0.0001	0.0136		
Missing Data	γ07	-0.0027	0.0063	0.0074	0.0114	-0.0048	0.0070
Enrollment*PreC	γ11			-0.0000	0.0000		
% Male*PreC	γ12			-0.0007	0.0017		
% Minoritized*PreC	γ13			0.0111	0.0201		
% FRL*PreC	γ14			-0.0011	0.0256		
Suburban*PreC	γ15			0.0062	0.0138		
Rural*PreC	γ16			0.0153	0.0160		
Missing Data * PreC	γ17			-0.0074	0.0177		
Enrollment*CY1	γ21			-0.0000	0.0000		
% Male*CY1	γ22			0.0001	0.0017		
% Minoritized *CY1	γ23			0.0168	0.0217		
% FRL*CY1	γ24			0.0060	0.0266		
Suburban*CY1	γ25			0.0004	0.0124		
Rural*CY1	γ26			-0.0026	0.0148		
Missing Data * CY1	γ27			-0.0247	0.0168		
Enrollment*CY2	γ31			0.0000	0.0000	0.0000	0.0001
% Male*CY2	γ32			0.0006	0.0019		
% Minoritized *CY2	γ33			-0.0098	0.0239		
% FRL*CY2	γ34			-0.0081	0.0288		
Suburban*CY2	γ35			-0.0054	0.0135		
Rural*CY2	γ36			0.0043	0.0161		
Missing Data * CY2	γ37			0.0329*	0.0163		
Random effects							
Residual	σ^2	0.0011		0.0010		0.0011	
Sch Intercept	U_{0i}	0.0006		0.0007		0.0007	
Sch CY1	U_{1i}	0.0004		0.0003		0.0003	
Sch CY2	U_{2i}	0.0005		0.0005		0.0004	
Model fit							
AIC		-2767.65		-2770.14		-2772.49	
BIC		-2683.78		-2588.43		-2702.60	
logLik		1401.82		1424.07		1401.25	
Deviance		-2803.65		-2848.14		-2802.49	
ICC		.3692		.3903		.3726	

Note. Sch = School, CY1 = COVID Year 1, CY2 = COVID Year 2, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch,, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

S. LOG-TRANSFORMED AND TRIMMED FULL SAMPLE MODEL

Table S1

Unconditional model parameters for log-transformed and trimmed model

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	γ00	1.1534**	0.0026	1.1490**	0.0040	1.1490**	0.0039
Pre-Covid	γ10			0.0019	0.0047	0.0020	0.0045
CY1	γ20			0.0133**	0.0046	0.0133**	0.0047
CY2	γ30			-0.0151**	0.0047	-0.0152**	0.0048
Random effects							
Residual	σ^2	0.0013		0.0012		0.0010	
Sch Intercept	U_{0i}	0.0007		0.0007		0.0008	
Sch CY1	U_{1i}					0.0005	
Sch CY2	U_{2i}					0.0006	
Model fit							
AIC		-2729.36		-2751.03		-2750.03	
BIC		-2715.43		-2723.16		-2698.94	
logLik		1367.68		1381.52		1386.02	
Deviance		-2735.36		-2763.03		-2772.03	
ICC		.3412		.3586		.4235	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2Sch = School. AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intraclass Correlation

Table S2
Conditional model parameters for log-transformed and trimmed model

Variable	Parameter	Model 4		Model 5		Final Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	γ00	1.1409**	0.0068	1.1397**	0.0100	1.1498**	0.0036
Pre-Covid	γ10	0.0016	0.0045	-0.0020	0.0125	0.0016	0.0045
Covid Year 1	γ20	0.0136**	0.0048	0.0150	0.0116	0.0138**	0.0048
Covid Year 2	γ30	-0.0153**	0.0048	-0.0179	0.0121	-0.0174**	0.0048
Enrollment	γ01	-0.0000	0.0000	0.0000	0.0000		
% Male	γ02	0.0002	0.0009	0.0005	0.0015		
% Minoritized	γ03	0.0195	0.0119	0.0132	0.0178		
% FRL	γ04	-0.0578**	0.0144	-0.0626**	0.0218	-0.0387**	0.0101
Suburban	γ05	0.0108	0.0072	0.0114	0.0118		
Rural	γ06	0.0081	0.0087	-0.0032	0.0137		
Missing Data	γ07	-0.0024	0.0065	0.0061	0.0116	-0.0040	0.0073
Enrollment*PreC	γ11			-0.0000	0.0000		
% Male*PreC	γ12			-0.0008	0.0017		
% Minoritized*PreC	γ13			-0.0005	0.0213		
% FRL*PreC	γ14			0.0088	0.0259		
Suburban*PreC	γ15			-0.0001	0.0146		
Rural*PreC	γ16			0.0064	0.0168		
Missing Data * PreC	γ17			-0.0075	0.0184		
Enrollment*CY1	γ21			-0.0000	0.0000		
% Male*CY1	γ22			0.0002	0.0017		
% Minoritized *CY1	γ23			0.0224	0.0221		
% FRL*CY1	γ24			0.0009	0.0272		
Suburban*CY1	γ25			0.0049	0.0132		
Rural*CY1	γ26			-0.0052	0.0163		
Missing Data * CY1	γ27			-0.0212	0.0178		
Enrollment*CY2	γ31			0.0000	0.0000	0.0092	0.0122
% Male*CY2	γ32			0.0002	0.0020		
% Minoritized *CY2	γ33			-0.0074	0.0259		
% FRL*CY2	γ34			-0.0129	0.0294		
Suburban*CY2	γ35			-0.0088	0.0142		
Rural*CY2	γ36			-0.0014	0.0169		
Missing Data * CY2	γ37			0.0310^{+}	0.0160		
Random effects							
Residual	σ^2	0.0010		0.0010		0.0010	
Sch Intercept	U_{0i}	0.0006		0.0006		0.0006	
Sch CY1	U_{1i}	0.0005		0.0004		0.0004	
Sch CY2	U_{2i}	0.0006		0.0006		0.0005	
Model fit							
AIC		-2767.32		-2449.10		-2704.22	
BIC		-2683.71		-2267.94		2639.19	
logLik		1401.66		1263.55		1366.11	
Deviance		-2803.32		-2527.10		-2732.22	
ICC		.3612		.3776		.3744	

Note. Sch = School, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

T. LOG-TRANSFORMED TFI SAMPLE MODEL

Table T1

Unconditional model parameters for log - transformed model (TFI)

Variable	Parameter	Model 1t		Model 2t		Model 3t	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	1.1477**	0.0032	1.1412**	0.0040	1.1412**	0.0036
Pre-Covid	$\gamma 10$			0.0029	0.0053	0.0029	0.0047
CY1	$\gamma 20$			0.0162**	0.0062	0.0162**	0.0065
CY2	$\gamma 30$			-0.0156**	0.0061	-0.0156**	0.0065
			Random effects				
Residual	σ^2	0.0014		0.0013		0.0009	
Sch Intercept	U_{0i}	0.0007		0.0007		0.0008	
Sch CY1	U_{1i}					0.0012	
Sch CY2	U_{2i}					0.0013	
			Model fit				
AIC		-1818.61		-1836.26		-1847.01	
BIC		-1805.80		-1810.67		-1800.05	
logLik		912.31		924.14		934.51	
Deviance		-1824.61		-1848.29		-1869.01	
ICC		.3390		.3588		.4662	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table T2

Conditional model parameters for log - transformed model (TFI)

Variable	Parameter	Model 4t		Model 5t	
		Estimate	*SE*	Estimate	*SE*
Intercept	$\gamma 00$	1.1404**	0.0098	1.1421**	0.0108
Pre-Covid	$\gamma 10$	0.0029	0.0047	-0.0061	0.0163
CY1	$\gamma 20$	0.0162*	0.0065	0.0219	0.0196
CY2	$\gamma 30$	-0.0156*	0.0065	-0.0041	0.0195
Meet TFI	$\gamma 01$	0.0010	0.0102	-0.0009	0.0114
Meet TFI*PreC	$\gamma 11$			0.0102	0.0167
Meet TFI*CY1	$\gamma 21$			-0.0065	0.0203
Meet TFI*CY2	$\gamma 31$			-0.0130	0.0203
Random effects					
Residual	σ^2	0.0009		0.0009	
Sch Intercept	U_{0i}	0.0008		0.0008	
Sch CY1	U_{1i}	0.0012		0.0012	
Sch CY2	U_{2i}	0.0013		0.0013	
Model Fit					
AIC		-1845.36		-1844.10	
BIC		-1794.13		-1780.06	
logLik		934.68		937.05	
Deviance		-1869.36		-1874.10	
ICC		.4652		.4701	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2 Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

U. LOG-TRANSFORMED AND TRIMMED TFI SAMPLE MODEL

Table U1

Unconditional model parameters for log-transformed and trimmed (TFI)

Variable	Parameter	Model 1t		Model 2t		Model 3t	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	1.1496**	0.0031	1.1434**	0.0039	1.1435**	0.0035
Pre-Covid	$\gamma 10$			0.0037	0.0054	0.0037	0.0047
CY1	$\gamma 20$			0.0136**	0.0062	0.0136**	0.0064
CY2	$\gamma 30$			-0.0140**	0.0061	-0.0141**	0.0065
Random effects							
Residual	σ^2	0.0014		0.0013		0.0008	
Sch Intercept	U_{0i}	0.0006		0.0006		0.0007	
Sch CY1	U_{1i}					0.0014	
Sch CY2	U_{2i}					0.0016	
Model fit							
AIC		-1811.16		-1824.65		-1843.27	
BIC		-1798.41		-1799.15		-1796.52	
logLik		908.58		918.32		932.63	
Deviance		-1817.16		-1839.65		-1865.27	
ICC		.3155		.3350		.4794	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table U2

Conditional model parameters for log-transformed and trimmed (TFI)

Variable	Parameter	Model 4t		Model 5t	
		Estimate	*SE*	Estimate	*SE*
Intercept	$\gamma 00$	1.1437**	0.0095	1.1421**	0.0102
Pre-Covid	$\gamma 10$	0.0037	0.0047	-0.0043	0.0177
CY1	$\gamma 20$	0.0136*	0.0064	0.0119	0.0218
CY2	$\gamma 30$	-0.0141*	0.0065	-0.0047	0.0194
Meet TFI	$\gamma 01$	-0.0002	0.0100	0.0016	0.0108
Meet TFI*PreC	$\gamma 11$			-0.0008	0.0180
Meet TFI*CY1	$\gamma 21$			0.0019	0.0226
Meet TFI*CY2	$\gamma 31$			-0.0106	0.0206
Random effects					
Residual	σ^2	0.0008		0.0008	
Sch Intercept	U_{0i}	0.0007		0.0007	
Sch CY1	U_{1i}	0.0014		0.0014	
Sch CY2	U_{2i}	0.0016		0.0015	
Model Fit					
AIC		-1841.66		-1839.30	
BIC		-1790.66		-1775.55	
logLik		932.83		934.65	
Deviance		-1865.66		-1869.30	
ICC		.4782		.4826	

Note. Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

V. MODEL WITHOUT IMPUTATION

Table V1

Unconditional model parameters without multiple imputation

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1664**	0.0067	3.1434**	0.0087	3.1456**	0.0086
Pre-Covid	$\gamma 10$			0.0135	0.0088	0.0091	0.0074
CY1	$\gamma 20$			0.0638**	0.0087	0.0653**	0.0084
CY2	$\gamma 30$			-0.0757**	0.0091	-0.0757**	0.0089
Random effects							
Residual	σ^2	0.0067		0.0054		0.0037	
Sch Intercept	U_{0i}	0.0065		0.0068		0.0090	
Sch CY1	U_{1i}					0.0035	
Sch CY2	U_{2i}					0.0030	
Model fit							
AIC		-1041.60		-1122.20		-1134.38	
BIC		-1028.38		-1095.76		-1085.90	
logLik		523.80		567.10		579.19	
Deviance		-1047.60		-1134.20		-1156.38	
ICC		.494		.556		.705	

Note. Sch = School. AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intraclass Correlation

Table V2

Unconditional model parameters without multiple imputation

Variable	Parameter	Model 4		Model 5		Final Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	γ00	3.1091**	0.0166	3.1359**	0.0216	3.1142**	0.0170
Pre-Covid	γ10	0.0089	0.0074	-0.0318	0.0204	0.0036	0.0083
Covid Year 1	γ20	0.0668**	0.0085	0.0748**	0.0199	0.0654**	0.0085
Covid Year 2	γ30	-0.0774**	0.0090	-0.0715**	0.0223	-0.0759**	0.0090
Enrollment	γ01	-0.0000	0.0000	0.0000	0.0001	-0.0000	0.0001
% Male	γ02	0.0006	0.0023	0.0026	0.0031		
% Minoritized	γ03	0.0809*	0.0312	0.0171	0.0407	0.0775*	0.0313
% FRL	γ04	-0.2013**	0.0371	-0.2184**	0.0501	-0.1976**	0.0372
Suburban	γ05	0.0440*	0.0177	0.0280	0.0248	0.0432*	0.0177
Rural	γ06	0.0386	0.0215	-0.0118	0.0290	0.0224	0.0245
Enrollment*PreC	γ11			-0.0000	0.0001		
% Male*PreC	γ12			-0.0034	0.0027		
% Minoritized*PreC	γ13			0.0502	0.0348		
% FRL*PreC	γ14			-0.0036	0.0440		
Suburban*PreC	γ15			0.0269	0.0235		
Rural*PreC	γ16			0.0764**	0.0269	0.0189	0.0149
Enrollment*CY1	γ21			-0.0001*	0.0001	-0.0001	0.0001
% Male*CY1	γ22			0.0005	0.0029		
% Minoritized *CY1	γ23			0.0544	0.0394		
% FRL*CY1	γ24			0.0380	0.0473		
Suburban*CY1	γ25			-0.0008	0.0227		
Rural*CY1	γ26			-0.0262	0.0272		
Enrollment*CY2	γ31			0.0001^{+}	0.0001	0.0000	0.0001
% Male*CY2	γ32			0.0024	0.0034		
% Minoritized *CY2	γ33			-0.0260	0.0439		
% FRL*CY2	γ34			-0.0056	0.0519		
Suburban*CY2	γ35			-0.0234	0.0259		
Rural*CY2	γ36			0.0241	0.0301		
Random effects							
Residual	σ^2	0.0037		0.0033		0.0036	
Sch Intercept	U_{0i}	0.0070		0.0071		0.0071	
Sch CY1	U_{1i}	0.0033		0.0021		0.0035	
Sch CY2	U_{2i}	0.0031		0.0026		0.0032	
Model fit							
AIC		-1159.65		-1164.01		-1159.44	
BIC		-1084.73		-1009.77		-1075.71	
logLik		596.83		617.01		598.72	
Deviance		-1193.65		-1234.01		-1197.44	
ICC		.656		.679		.664	

Note. Sch = School, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

W. MODEL WITH DISAGGREGATED RACIAL COMPOSITION

Table W1

Unconditional model parameters with disaggregated school-level racial composition

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1659**	0.0070	3.1512**	0.0087	3.1512**	0.0091
Pre-Covid	$\gamma 10$			0.0068	0.0088	0.0068	0.0090
CY1	$\gamma 20$			0.0442**	0.0087	0.0442**	0.0097
CY2	$\gamma 30$			-0.0500**	0.0091	-0.0500**	0.0099
Random effects							
Residual	σ^2	0.0073		0.0067		0.0054	
Sch Intercept	U_{0i}	0.0068		0.0070		0.0080	
Sch CY1	U_{1i}					0.0030	
Sch CY2	U_{2i}					0.0021	
Model fit							
AIC		-1318.71		-1331.86		-1365.40	
BIC		-1304.73		-1303.91		-1314.15	
logLik		662.35		671.93		693.70	
Deviance		-1324.71		-1343.86		-1387.40	
ICC		.4855		.5129		.5950	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School. AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intraclass Correlation

Table W1

Conditional model parameters with disaggregated school-level racial composition

Variable	Parameter	Model 4		Model 5		Final Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	γ_{00}	3.1397**	0.0185	3.1543**	0.0241	3.1537**	0.0109
Pre-Covid	γ_{10}	0.0064	0.0091	-0.0262	0.0264	0.0050	0.0101
Covid Year 1	γ_{20}	0.0447**	0.0098	0.0708**	0.0260	0.0672**	0.0094
Covid Year 2	γ_{30}	-0.0502**	0.0099	-0.0755**	0.0263	-0.0781**	0.0099
Enrollment	γ_{01}	-0.0001^{+}	0.0001	-0.0001	0.0001	-0.0001	0.0001
% Male	γ_{02}	0.0004	0.0024	0.0014	0.0033		
% AI / NA	γ_{03}	-0.0164	0.0946	-0.0446	0.1143	-0.0407	0.0897
% Asian / PI	γ_{04}	0.0886	0.1532	0.0877	0.2407	0.0992	0.1462
% Black / AA	γ_{05}	-0.0417	0.0466	-0.1441*	0.0588	-0.0459	0.0443
% Latine	γ_{06}	0.0443	0.0374	0.0042	0.0492	0.0620	0.0360
% NA / OPI	γ_{07}	-0.9507	0.9465	0.3578	1.1334	-0.5685	0.9185
% Multiracial	γ_{08}	-0.4452^{+}	0.2426	-0.5781^{+}	0.3258	-0.4291^{+}	0.2326
% FRL	γ_{09}	-0.1660**	0.0436	-0.1411*	0.0593	-0.1653**	0.0417
Suburban	γ_{010}	0.0240	0.0195	0.0093	0.0268		
Rural	γ_{011}	-0.0085	0.0260	-0.0484	0.0349	-0.0309	0.0240
Missing Data	γ_{012}	-0.0047	0.0118	0.0139	0.0211	0.0185	0.0161
Enrollment * PreC	γ_{11}			0.0000	0.0001		
% Male* PreC	γ_{12}			-0.0022	0.0035		
% AI / NA* PreC	γ_{13}			-0.0038	0.1530		
% Asian / PI* PreC	γ_{14}			0.1213	0.2387		
% Black / AA* PreC	γ_{15}			0.0961	0.0655		
% Latine * PreC	γ_{16}			0.0418	0.0504		
% NH / OPI* PreC	γ_{17}			-1.2257	1.6156		
% Multiracial * PreC	γ_{18}			0.1360	0.3361		
% FRL* PreC	γ_{19}			-0.0237	0.0635		
Suburban* PreC	γ_{110}			0.0269	0.0296		
Rural* PreC	γ_{111}			0.0657^{+}	0.0377	0.0121	0.0167
Missing Data * PreC	γ_{112}			0.0026	0.0358		
Enrollment * CY1	γ_{21}			-0.0001	0.0001		
% Male * CY1	γ_{22}			0.0004	0.0035		
% AI / NA * CY1	γ_{23}			0.0295	0.1527		
% Asian / PI * CY1	γ_{24}			-0.1874	0.2132		
% Black / AA* CY1	γ_{25}			0.0674	0.0687		
% Latine * CY1	γ_{26}			0.0546	0.0539		
% NH / OPI * CY1	γ_{27}			0.4042	1.6156		
% Multiracial * CY1	γ_{28}			-0.0197	0.3520		
% FRL * CY1	γ_{29}			-0.0002	0.0629		
Suburban * CY1	γ_{210}			-0.0008	0.0296		
Rural * CY1	γ_{211}			-0.0143	0.0373		
Missing Data * CY1	γ_{212}			-0.0885**	0.0332	-0.0939**	0.0247
Enrollment * CY2	γ_{31}			0.0001	0.0001		
% Male * CY2	γ_{32}			0.0013	0.0039		
% AI / NA * CY2	γ_{33}			0.0011	0.1649		
% Asian / PI * CY2	γ_{34}			0.1101	0.2167		
% Black / AA* CY2	γ_{35}			0.0188	0.0733		
% Latine * CY2	γ_{36}			-0.0249	0.0577		
% NH / OPI * CY2	γ_{37}			-1.6957	1.5587		
% Multiracial * CY2	γ_{38}			0.3391	0.3675		

Table W1 Cont.

% FRL * CY2	$\gamma 39$			-0.0437	0.0650		
Suburban * CY2	$\gamma 310$			-0.0119	0.0301		
Rural * CY2	$\gamma 311$			0.0299	0.0384		
Missing Data * CY2	$\gamma 312$			0.0931**	0.0344	0.1115**	0.0319
Random effects							
Residual	σ^2	0.0055		0.0052		0.0053	
Sch Intercept	U_{0i}	0.0056		0.0057		0.0054	
Sch CY1	U_{1i}	0.0028		0.0018		0.0021	
Sch CY2	U_{2i}	0.0020		0.0019		0.0022	
Model fit							
AIC		-1295.18		-1116.51		-1425.73	
BIC		-1187.02		-841.61		-1313.91	
logLik		670.09		617.26		736.87	
Deviance		-1340.18		-1234.51		-1473.73	
ICC		.5033		.5240		.5083	

Note. Sch = School, Male = school composition of male students, AI / NA = school composition of American Indian / Native American students, Asian / PI = school composition of Asian or Pacific Islander students, Black / AA = school composition of Black or African American students, Latine = school composition of Latine students, NH/OPI = school composition of Native Hawaiian or Other Pacific Islander students, Multiracial = school composition of multiracial students, FRL = school composition of students receiving free or reduced lunch,, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

X. MODEL WITH SCHOOLS WITH OVER ONE SURVEY

Table X1

Unconditional model parameters for schools with over one survey

Variable	Parameter	Model 1s		Model 2s		Model 3s	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	γ00	3.1639**	0.0072	3.1475**	0.0096	3.1475**	0.0097
Pre-Covid	γ10			0.0097	0.0102	0.0097	0.0096
CY1	γ20			0.0438**	0.0102	0.0438**	0.0104
CY2	γ30			-0.0512**	0.0104	-0.0512**	0.0100
Random effects							
Residual	σ^2	0.0086		0.0079		0.0066	
Sch Intercept	U_{0i}	0.0075		0.0077		0.0092	
Sch CY1	U_{1i}					0.0035	
Sch CY2	U_{2i}					0.0010	
Model fit							
AIC		-1267.85		-1310.14		-1314.60	
BIC		-1253.71		-1281.85		-1262.74	
logLik		636.93		661.07		668.30	
Deviance		-1273.85		-1322.14		-1336.60	
ICC		.4664		.4912		.5835	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table X2

Conditional model parameters for schools with over one survey

Variable	Parameter	Model 4s Estimate	Model 4s SE	Model 5s Estimate	Model 5s SE	Final S Model Estimate	Final S Model *SE*
Intercept	γ00	3.1106**	0.0183	3.1165**	0.0242	3.1024**	0.0178
Pre-Covid	γ10	0.0094	0.0096	-0.0164	0.0256	0.0112	0.0095
Covid Year 1	γ20	0.0441**	0.0104	0.0690**	0.0256	0.0656**	0.0099
Covid Year 2	γ30	-0.0513**	0.0100	-0.0631*	0.0249	-0.0771**	0.0101
Enrollment	γ01	0.0000	0.0001	0.0001	0.0001		
% Male	γ02	-0.0001	0.0026	0.0009	0.0036		
% Minoritized	γ03	0.0004	0.0003	-0.0002	0.0005		
% FRL	γ04	-0.0016**	0.0004	-0.0013*	0.0006	-0.0012**	0.0003
Suburban	γ05	0.0455*	0.0198	0.0384	0.0284	0.0561**	0.0187
Rural	γ06	0.0440^{+}	0.0239	0.0195	0.0329	0.0332	0.0212
Missing Data	γ07	-0.0031	0.0128	0.0191	0.0233	0.0199	0.0170
Enrollment*PreC	γ11			-0.0000	0.0001		
% Male*PreC	γ12			-0.0022	0.0035		
% Minoritized *PreC	γ13			0.0007	0.0005		
% FRL*PreC	γ14			-0.0006	0.0006		
Suburban*PreC	γ15			0.0226	0.0297		
Rural*PreC	γ16			0.0514	0.0349		
Missing Data * PreC	γ17			-0.0002	0.0362		
Enrollment*CY1	γ21			-0.0001	0.0001		
% Male*CY1	γ22			0.0004	0.0036		
% Minoritized *CY1	γ23			0.0005	0.0005		
% FRL*CY1	γ24			0.0002	0.0006		
Suburban*CY1	γ25			0.0008	0.0284		
Rural*CY1	γ26			-0.0105	0.0347		
Missing Data * CY1	γ27			-0.0928	0.0333	-0.0894**	0.0266
Enrollment*CY2	γ31			0.0001	0.0001		
% Male*CY2	γ32			0.0018	0.0037		
% Minoritized *CY2	γ33			-0.0003	0.0006		
%FRL*CY2	γ34			-0.0002	0.0006		
Suburban*CY2	γ35			-0.0257	0.0290		
Rural*CY2	γ36			-0.0058	0.0349		
Missing Data*CY2	γ37			0.1122**	0.0332	0.1042**	0.0326
Random effects							
Residual	σ^2	0.0066		0.0061		0.0064	
Sch Intercept	U_{0i}	0.0074		0.0077		0.0077	
Sch CY1	U_{1i}	0.0033		0.0020		0.0023	
Sch CY2	U_{2i}	0.0010		0.0013		0.0012	
Model fit							
AIC		-1335.16		-1347.33		-1361.19	
BIC		-1250.29		-1163.48		-1281.05	
logLik		685.57		712.66		697.60	
Deviance		-1371.15		-1425.33		-1395.19	
ICC		.5286		.5546		.5444	

Note. Sch = School, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Y. MODEL WITH WEIGHT OF TOTAL ENROLLMENT

Table Y1

Unconditional model parameters with weight of total enrollment

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1663**	0.0069	3.1539**	0.0091	3.1530**	0.0090
Pre-Covid	$\gamma 10$			0.0062	0.0095	0.0062	0.0085
CY1	$\gamma 20$			0.0386**	0.0099	0.0407**	0.0098
CY2	$\gamma 30$			-0.0465**	-0.0101	-0.0475**	0.0102
Random effects							
Residual	σ^2	3.0601		2.8396		2.0607	
Sch Intercept	U_{0i}	0.0066		0.0067		0.0082	
Sch CY1	U_{1i}					0.0043	
Sch CY2	U_{2i}					0.0041	
Model fit							
AIC		-1318.16		-1355.94		-1369.66	
BIC		-1304.18		-1327.98		-1318.40	
logLik		662.08		683.97		695.83	
Deviance		-1324.16		-1367.94		-1391.66	
ICC		.0021		.0024		.0040	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table Y2
Conditional model parameters with weight of total enrollment

Variable	Parameter	Model 4		Model 5		Final Weighted Model	
		Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
Intercept	$\gamma 00$	3.1231**	0.0178	3.1252**	0.0240	3.1337**	0.0120
Pre-Covid	$\gamma 10$	0.0057	0.0085	-0.0150	0.0258	0.0079	0.0085
Covid Year 1	$\gamma 20$	0.0415**	0.0099	0.0710**	0.0249	0.0638**	0.0095
Covid Year 2	$\gamma 30$	-0.0479**	0.0102	-0.0689**	0.0266	-0.0744**	0.0102
Enrollment	$\gamma 01$	-0.0000	0.0000	0.0000	0.0001		
% Male	$\gamma 02$	0.0005	0.0025	0.0015	0.0033		
% Minoritized	$\gamma 03$	0.0006^{+}	0.0003	0.0004	0.0004	0.0005	0.0003
% FRL	$\gamma 04$	-0.0019**	0.0004	-0.0021**	0.0005	-0.0018**	0.0004
Suburban	$\gamma 05$	0.0382*	0.0191	0.0349	0.0273	0.0235	0.0150
Rural	$\gamma 06$	0.0297	0.0232	0.0064	0.0320		
Missing Data	$\gamma 07$	-0.0052	0.0118	0.0132	0.0204	0.0166	0.0159
Enrollment*PreC	$\gamma 11$			-0.0000	0.0001		
% Male*PreC	$\gamma 12$			-0.0027	0.0033		
% Minoritized *PreC	$\gamma 13$			0.0003	0.0004		
% FRL*PreC	$\gamma 14$			0.0001	0.0005		
Suburban*PreC	$\gamma 15$			0.0162	0.0287		
Rural*PreC	$\gamma 16$			0.0495	0.0348		
Missing Data * PreC	$\gamma 17$			-0.0000	0.0345		
Enrollment*CY1	$\gamma 21$			-0.0001	0.0001		
% Male*CY1	$\gamma 22$			0.0005	0.0038		
% Minoritized *CY1	$\gamma 23$			0.0004	0.0005		
% FRL*CY1	$\gamma 24$			0.0003	0.0006		
Suburban*CY1	$\gamma 25$			-0.0006	0.0287		
Rural*CY1	$\gamma 26$			-0.0205	0.0345		
Missing Data * CY1	$\gamma 27$			-0.0845**	0.0324	-0.0871**	0.0249
Enrollment*CY2	$\gamma 31$			0.0001	0.0001		
% Male*CY2	$\gamma 32$			0.0026	0.0042		
% Minoritized *CY2	$\gamma 33$			-0.0003	0.0005		
% FRL*CY2	$\gamma 34$			-0.0003	0.0006		
Suburban*CY2	$\gamma 35$			-0.0196	0.0300		
Rural*CY2	$\gamma 36$			0.0171	0.0369		
Missing Data*CY2	$\gamma 37$			0.1022**	0.0327	0.0999**	0.0320
Random effects							
Residual	σ^2	2.0523		1.9092		1.9960	
Sch Intercept	U_{0i}	0.0063		0.0065		0.0066	
Sch CY1	U_{1i}	0.0043		0.0029		0.0033	
Sch CY2	U_{2i}	0.0041		0.0038		0.0042	
Model fit							
AIC		-1392.79		-1410.54		-1419.07	
BIC		-1308.92		-1228.83		-1339.87	
logLik		714.39		744.27		726.54	
Deviance		-1428.79		-1488.54		-1453.08	
ICC		.0031		.0034		.0033	

Note. Sch = School, Male = school composition of male students, Minoritized = school composition of racially and ethnically minoritized students, FRL = school composition of students receiving free or reduced lunch, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Z. MODEL WITH SCHOOLS WITH OVER ONE SURVEY (TFI)

Table Z1

Unconditional model parameters with over one survey (TFI)

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	$\gamma 00$	3.1526**	0.0086	3.1299**	0.0107	3.1299**	0.0106
Pre-Covid	$\gamma 10$			0.0124	0.0120	0.0124	0.0107
CY1	$\gamma 20$			0.0524**	0.0128	0.0524**	0.0133
CY2	$\gamma 30$			-0.0510**	0.0126	-0.0510**	0.0121
Random effects							
Residual	σ^2	0.0094		0.0086		0.0065	
Sch Intercept	U_{0i}	0.0074		0.0076		0.0094	
Sch CY1	U_{1i}					0.0058	
Sch CY2	U_{2i}					0.0021	
Model fit							
AIC		-825.66		-859.33		-865.10	
BIC		-812.65		-833.32		-817.41	
logLik		415.83		435.67		443.55	
Deviance		-831.66		-871.33		-887.10	
ICC		.4411		.4712		.5895	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table Z2
Unconditional model parameters with over one survey (TFI)

Variable	Parameter	Model 4		Model 5	
		Estimate	SE	Estimate	SE
Intercept	γ00	3.1321**	0.0277	3.1343**	0.0325
Pre-Covid	γ10	-0.0124	0.0107	-0.0057	0.0378
CY1	γ20	0.0524**	0.0133	0.0588	0.0448
CY2	γ30	-0.0510**	0.0121	-0.0131	0.0413
Meet TFI	γ01	-0.0025	0.0287	-0.0049	0.0344
TFI*PreC	γ11			0.0202	0.0394
TFI*CY1	γ21			-0.0071	0.0471
TFI*CY2	γ31			-0.0424	0.0436
Random effects					
Residual	σ^2	0.0065		0.0064	
Sch Intercept	U_{0i}	0.0094		0.0094	
Sch CY1	U_{1i}	0.0058		0.0059	
Sch CY2	U_{2i}	0.0021		0.0020	
Model fit					
AIC		-863.233		-861.16	
BIC		-811.21		-796.14	
logLik		443.62		445.58	
Deviance		-887.23		-891.16	
ICC		.5894		.5918	

Unconditional model parameters with over one survey (TFI)
Note. Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

AA. MODEL WITH WEIGHT OF TOTAL ENROLLMENT (TFI)

Table AA1

Unconditional model parameters with weight of total enrollment

Variable	Parameter	Model 1		Model 2		Model 3	
		Estimate	SE	Estimate	SE	Estimate	*SE*
Intercept	γ00	3.1541**	0.0083	3.1371**	0.0101	3.1354**	0.0097
Pre-Covid	γ10			0.0088	0.0113	0.0088	0.0093
CY1	γ20			0.0437**	0.0131	0.0475**	0.0132
CY2	γ30			-0.0460**	-0.0127	-0.0476**	0.0127
Random effects							
Residual	σ^2	3.2990		3.0306		1.8636	
Sch Intercept	U_{0i}	0.0063		0.0064		0.0079	
Sch CY1	U_{1i}					0.0067	
Sch CY2	U_{2i}					0.0062	
Model fit							
AIC		-863.69		-891.47		-911.13	
BIC		-850.85		-865.85		-864.17	
logLik		434.85		451.73		466.57	
Deviance		-869.69		-903.47		-933.13	
ICC		.0019		.0021		.0043	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

Table AA2
Conditional model parameters with weight of total enrollment

Variable	Parameter	Model 4		Model 5	
		Estimate	SE	Estimate	SE
Intercept	γ00	3.1324**	0.0256	3.1288**	0.0290
Pre-Covid	γ10	0.0088	0.0093	-0.0104	0.0329
CY1	γ20	0.0476**	0.0132	0.0709+	0.0397
CY2	γ30	-0.0476**	0.0127	-0.0046	0.0372
Meet TFI	γ01	0.0034	0.0268	0.0076	0.0307
TFI*PreC	γ11			0.0216	0.0338
TFI*CY1	γ21			-0.0265	0.0420
TFI*CY2	γ31			-0.0484	0.0394
Random effects					
Residual	σ^2	1.8509		1.8920	
Sch Intercept	U_{0i}	0.0079		0.0078	
Sch CY1	U_{1i}	0.0068		0.0065	
Sch CY2	U_{2i}	0.0063		0.0058	
Model fit					
AIC		-909.52		-909.54	
BIC		-858.29		-845.50	
logLik		466.76		469.77	
Deviance		-933.52		-939.54	
ICC		.0043		.0042	

Note. CY1 = COVID Year 1, CY2 = COVID Year 2, Sch = School, AIC = Akaike Information Criteria, BIC = Bayesian Information Criterion, logLike = Log-Likelihood Value, ICC = Intra-Class Correlation

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