Fall 2021

Advancing Research Methodology and Educational Policy: An Application of Mixture Modeling Using School Climate

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ADVANCING RESEARCH METHODOLOGY AND EDUCATIONAL POLICY: AN APPLICATION OF MIXTURE MODELING USING SCHOOL CLIMATE

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Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Educational Psychology and Research

College of Education

University of South Carolina

2021

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DEDICATION

To Gage (my heart), my parents (my home), my grandparents (my inspiration), and my Aunt Kathy (my biggest advocate).

ACKNOWLEDGEMENTS

This work would not have been possible without the guidance and support from my dissertation committee. I would like to especially recognize my advisor and committee chair, Dr. Christine DiStefano. As an advisor and teacher, you elevated my understanding of measurement and helped me to gain valuable experiences outside of the department that prepared me for my career. As my chair, your insight, feedback, and positive encouragement were vital to the completion of this work. Thank you for helping me achieve my goals both within and outside of the program.

I would also like to acknowledge my supervisor and colleagues at the South Carolina Education Policy Center (SCEPC), specifically Dr. Monrad, Elizabeth Leighton, and Dr. Mihaela Ené. I would not be where I am today without your guidance and support throughout this program. Thank you for teaching me so many valuable lessons that I will carry with me in my professional career. You are the best team I could have asked for, and I am proud to call you friends in addition to colleagues. I would like to recognize my partner in coffee runs, Dawn Coleman. I would not have made it through this program without you. Thank you for always being my sounding board. I am so thankful that we met through this program and are now great friends.

Finally, I would like to acknowledge my partner, family, and friends for being a source of love and light throughout this program and for always encouraging me to do my best and to keep pushing forward. I am so grateful for you all.

ABSTRACT

School climate is a well-studied issue in educational research. However, surveys of school climate tend to be analyzed using item-centered as opposed to person-centered methods. The current study evaluated the 2018 South Carolina School Climate Survey using advanced applications of mixture modeling in an attempt to identify latent profiles at the student and school levels. The relatively new manual BCH 3-Step approach was applied given its usefulness in analyzing multilevel data with covariates and distal outcomes. However, its application to multilevel mixture models leaves room for advancement and prompted the adoption of an alternative analysis plan that included separate analyses for students and schools.

A latent profile analysis was conducted at the student level and resulted in the identification of six student profiles. At the school level, the manual BCH 3-Step process was applied, allowing for the incorporation of a covariate for school poverty level and distal outcomes related to academic achievement. Two profiles were identified at the school level, but because schools were also assigned to 'known classes' based on type (elementary, middle, high), a total of six profiles were created and analyzed in relation to the covariate and distal outcomes. A discussion of the results and methodological challenges associated with this study follows alongside considerations about how school climate can and should be analyzed, interpreted, and applied from both methodological and policy perspectives.

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CHAPTER 1

INTRODUCTION

Education systems provide youth with an opportunity to learn a variety of social and academic skills as they prepare for the responsibilities that accompany adulthood. However, a variety of factors can impact the quality of learning. These factors may be positive (e.g., strong student-teacher relationships, small class size) or negative (e.g., poverty, unsafe physical environment), and can exist within school walls or can extend beyond a school's property line. It is the job of our educational and governmental institutions to identify and correct those factors that pose a risk to student progress. One tool for pinpointing and monitoring threats to a quality learning environment is the measurement of the school's climate.

School Climate

School climate can be defined as a school's personality that reflects the collective perceptions of school members such as teachers, students, and parents (Hoy & Miskel, 2013). The benefits of positive school climate are well-documented and have contributed to educational policies and reforms for the past three decades (Thapa et al., 2012). Positive school climate is linked to improved student academic achievement (Greenberg, 2004; Lee & Burkam,1996; Stewart, 2008), increased teacher job satisfaction (Ma & MacMillan, 1999), and enhanced home-school relationships (DiStefano et al., 2007). It is also associated with improved child and youth development, successful risk prevention

and health promotion efforts, higher student graduation rates, and increased teacher retention (Thapa, 2013).

Apart from the impact that school climate has on a variety of factors, there are also several issues that can impact measurements of school climate. For example, student and regional poverty can have a substantial impact on academic achievement and student engagement (Darling-Hammond & Cook-Harvey, 2018). Poverty can also be closely tied to the amount of social capital in the surrounding community. Schools are social systems at their core and are therefore affected by their surrounding environment (Hoy & Miskel, 2013). Investments of money, resources, or time made by local businesses and the community at large can greatly contribute to a school's physical and social climate (Hoy & Miskel, 2013). By the same token, impoverished schools without these relationships may not experience the same improvements to their school climate.

The consistency and quality of school leadership can also impact school climate (Cohen et al., 2009; Hoy & Miskel, 2013). A principal's leadership style can either facilitate or obstruct improvements in teaching and learning which then impact school climate (Al-Jabari, 2004). Levels of school engagement, teacher/staff relationships, management of the physical and social environment, and support relayed to teachers and students all contribute to a positive climate and are largely the responsibility of the school administration and principal (Noonan, 2004). Schools with greater rates of principal turnover are associated with lower student test scores, poor student/parent perceptions of discipline and order, and decreased participation in school activities among parents (Griffith, 1999). Principal leadership behaviors can influence teachers' commitment to

improve teaching practices while also facilitating more peaceful working conditions (Al-Jabari, 2014; Balyer, 2012).

The above discussion illustrates that a complex system is at play as it relates to student achievement and school climate. Climate is affected by and impacts a variety of factors, some of which are beyond the control of a school or its employees; but the advantage of using school climate as an indicator of school quality is its malleability (Voight et al., 2013). In other words, teachers, schools, and districts have the ability to adopt practices to foster an environment where students feel safe and engaged in learning independent of the factors that may negatively influence student success within and beyond the classroom (e.g., poverty, unstable home environment) (Thapa et al., 2013).

The manageable nature of school climate compared to other barriers to academic achievement (e.g., school poverty levels) makes climate a popular target of school reform initiatives. Further, school climate data is versatile in that it allows schools to monitor progress, make data-based decisions, collaborate with important stakeholders, and continuously adapt and modify their approach according to the school's current needs (National Center on Safe and Supportive Learning Environments, n.d.).

This versatility together with the multitude of benefits of a positive school climate have resulted in the creation and application of hundreds of school climate surveys in the United States (Cohen et al., 2009). However, these surveys are rarely applied to meet state or federal accountability measures. As of 2018, only eight states had included school climate in their state accountability systems (Kostyo et al., 2018). A total of 16 states currently have strategies for improving school climate via efforts such as improving technical assistance or supporting processes of diagnostic/self-assessment

(Kostyo et al., 2018). Twelve states outside of the aforementioned 24 collect and report on school climate data for other purposes, while the remaining six states do not appear to be using a school climate instrument for any purpose (Kostyo et al., 2018).

However, even if every state opted to assess school climate, the measurement of the construct could vary considerably across states, districts, and schools. School surveys can vary both in their focus as well as their respondents. Student surveys may aim to analyze students' perceptions of their learning experiences, relationships with teachers, or feelings of safety with the aim of improving their academic achievement. The emphasis of parent surveys may be parents' level of involvement with the school or relationships with teachers and principals in an effort to create an engaging learning community within and outside of school. In contrast, teacher/personnel surveys can center on issues of training, school leadership, and student discipline to provide insight into teacher retention rates, burnout, or teachers' perceptions of self-efficacy (Taylor & Tashakkori, 1995). Each of these issues can be measured differently within each respondent group, making the operationalization of the construct even more complex.

The multifaceted construct of school climate has undoubtedly yielded a broad range of operationalizations. However, over time, several broad domains have emerged in school climate research including safety, relationships, teaching, learning, and external environment (Thapa et al., 2012; Van Eck et al., 2017). In current practice, the most common domains measured in state school surveys include engagement, academic expectations and rigor, positive relationships, physical and emotional safety, bullying, discipline and order, mental and physical health, and equity and cultural respect (Jordan & Hamilton, 2020).

A compendium of school climate surveys recommended by the U.S. Department of Education's Office of Safe and Healthy Students (United States Department of Education, Office of Safe and Healthy Students (DOE-OSHS), 2018) underscores similar domains. Suggested instruments included but were not limited to the California Healthy Kids Survey, the Consortium on Chicago School Research Survey of Chicago Public Schools, and the Comprehensive School Climate Inventory (CSCI) (see DOE-OSHS, 2018 for a complete inventory). In total, 23 student, 20 staff, and 11 family surveys were recommended to measure school climate (DOE-OSHS, 2018). Common constructs measured within the student surveys included student engagement, levels of involvement (teacher, student, family), bullying, the environment (physical and disciplinary), types of behavior, and relationships. Popular constructs among staff surveys were student behavior, environment (discipline, physical), community/parent involvement, available supports, learning, leadership, relationships, safety, and engagement (teachers/students). For parents, issues of bullying, the environment (learning, physical), safety, available supports, school culture, discipline, and relationships were prevalent.

The school climate surveys within the aforementioned compendium provide insight as to the operationalization of school climate in the United States. While there is some overlap in the measured constructs within each instrument, the type, quality, and intended applications of each instrument are unique. The following section discusses the unique measurement and applications of school climate in South Carolina (SC).

School Climate in South Carolina

South Carolina measures school climate and has historically used climate scores as an ESSA accountability measure.[1] School climate surveys are administered in all public schools which then use results to gauge yearly progress, inform future decisions, and meet requirements of the state's accountability legislation. Students, teachers, and parents are surveyed to assess schools' respective school climate performance.

Even though students, teachers, and parents in every SC public school receive an extensive school climate survey, only six items are included in the state's annual school report card. For accountability purposes, schools are rated based on their performance on a number of indicators, specifically academic achievement, student progress, preparing for success, student engagement, English learners' proficiency progress, graduation rate, and college/career readiness. However, while school climate items are reported as indicators for student engagement and student safety, they are not incorporated into each school's rating.

Apart from use in the state's district and school report card, data from the school climate surveys are evaluated each year by the South Carolina Education Policy Center at the University of South Carolina. Profiles of schools are created and examined with school and district leaders to aid their understanding of yearly progress and their position relative to similar schools in the state and their respective districts. These meetings have proven to be an invaluable resource in helping administrators track their progress and locate areas where greater focus is needed. They have also prompted numerous studies of

[1] As of the 2020-2021 school year, South Carolina no longer uses a school climate survey as an ESSA accountability measure. While student engagement was used in lieu of school climate in the 2019-2020 school year, it is also no longer being used.

SC school climate data using a variety of analytical procedures, contributing the relevant literature. Details of the analytical practices within the scope of the school climate literature are discussed in the following section.

The Analysis of School Climate

As previously discussed, there is currently no universal definition for or operationalization of the construct of school climate. And within a single operationalization, the manner in which researchers measure school climate may still vary. Despite the numerous ways of defining school climate, the range of methodologies applied to the study of school climate is comparably narrow. Most studies of school climate use variable-centered methodologies such as factor analysis that focus on the relationships among variables and assume the presence of a single, homogenous population with respect to how predictor variables function in relation to the outcome variables (Laursen & Hoff, 2006).

However, person-centered methodologies such as latent profile analysis are far less common. Profiles of students and schools can provide valuable insight into the innerworkings of schools and the challenges they face in meeting accountability and achievement standards. Many studies of school climate also fail to account for the natural nesting of educational data (e.g., students within schools) through the use of multilevel models. It is important to account for the nesting of data when attempting to identify latent profiles to avoid inaccuracy and bias in parameter estimation (Makikangas et al., 2018).

Applications of multilevel, person-centered studies of school climate are all the more absent from the literature, and those using multilevel latent profile analysis (MLPA)

are largely missing. Unfortunately, the failure to recognize the multilevel structure of nested data can give rise to inaccurate results and improper conclusions regarding the population of interest. These observations also hold for past studies of SC school climate student surveys and pinpoints a gap in the literature

The proposed study seeks to fill gaps in the existing literature by investigating the following research questions:

1. What types of school climate profiles are uncovered at both the student and school levels and:
    (a) how does school poverty impact each identified latent profile?
    (b) do identified profiles perform similarly with regard to academic achievement and college/career readiness indicators?
2. How useful are profiles created using a large number of items rather than aggregated scores (e.g., factor scores) in terms of application and interpretability:
    (a) from a methodological perspective?
    (b) from a policy perspective?
3. Is the manual BCH 3-Step, and more generally mixture modeling, an effective way to analyze school climate data:
    (a) from a methodological perspective?
    (b) from a policy perspective?

In answering the above questions, the current study will provide a view of SC school climate through a person-centered and multilevel lens that has not been examined up to this point. It also seeks to assess the usefulness of such methods in settings outside of measurement. More specifically, it aims to shed light on what choices make person-

centered methodologies such as mixture modeling a practical and effective tool for those in the policy arena.

Currently, variable-centered measures of school climate are used by the state and its research partners to compare school performance on climate measures. This approach helps researchers and policymakers to evaluate each school's success in fostering a positive school climate, but it does not recognize the naturally heterogenous populations within schools and across the state. The result is a fairly limited view of the construct of school climate is and how it currently operates in South Carolina.

While state education departments have yet to adopt a person-centered approach in their evaluation of school climate, other organizations can work with schools to apply this approach. Currently, the South Carolina Education Policy Center (SCEPC) assists schools in evaluating their school climate performance. Part of this evaluation includes a comparison of each school to "similar schools" that share a similar range of poverty indexes (a SC poverty measure) and grade level. The application of MLPA can provide more detailed student and school groupings that allow for a more accurate comparison of schools' climate performance.

The identification of latent school climate profiles can also inform current practices by which school climate is included in state accountability measures. Presently, state report cards present an overgeneralized view of school climate. Items measuring perceptions of school climate on the report card are restricted to three items for students and five items for parents and teachers, failing to utilize additional information collected as part of the 51-item climate survey. Further, only the average response for each item is reported. While standard deviations can be included, item-centered methods largely

neglect the variability of responses within and across items at each school. The result is an oversimplification of how school climate is incorporated into South Carolina's accountability measures. As the inclusion of a complete list of school climate indicators in the report card has yet to occur, the inclusion of profiles at the student and school levels can serve as a tenable alternative that provides greater detail as to a school's climate performance without overgeneralizing the construct.

Overall, the current study aims to contribute to the sparse literature regarding the identification of latent profiles in the context of school climate. Grouping students and schools by shared characteristics can help policymakers and school administrators better understand and address the variety of challenges our students and schools face on a daily basis. It can also aid in the proper distribution of district and state services that can be better targeted to schools with varying combinations of student climate profiles.

Furthermore, while the current study is limited to the analysis of mixture modeling applications within the context of school climate, lessons learned from this analysis can and should be extended to other areas within and outside of education. Surveys are pervasive in today's society, appearing in fields of education, psychology, medicine, and economics (to name a few). And it is their ubiquity that should compel researchers to continuously expand how their data are analyzed and presented to the public, as illustrated in the present study.

The organization of the current study is as follows. Chapter 2 is devoted to an analysis of the relevant literature pertaining to both school climate and methodology. Chapter 3 describes the adopted methods and provides details of the sample and instrument. Chapter 4 provides an extensive review of the results for each methodological

procedure. Chapter 5 concludes the paper with an examination of the practical and theoretical implications of the results, final conclusions, observed limitations, and suggestions for further research.

CHAPTER 2

LITERATURE REVIEW

This chapter is devoted to the review of the literature and methodologies applied within the purview of school climate. More specifically, it seeks to highlight the importance of the measurement of school climate as well as a need for person-centered research in this area. The first section provides important background information on school climate as well as its general and specific applications within the United States and South Carolina, respectively. A review of the appropriate practices and relevant literature surrounding LPA and MLPA follows. This chapter concludes with a discussion of the role of the current study and how it relates to the current literature on MLPA and enhancing the study of school climate through advanced measurement applications.

School Climate

To fully understand the construct of school climate, one must first consider its history. The first recognized work involving school climate was by Arthur C. Perry (1908) who discussed the importance of positive climate in improving productivity, functionality, and a sense of community within a school (Chirkina & Khavenson, 2018; Freiberg, 1999). However, at this point in time, most researchers were focusing their attentions on organizational climate and employee motivation. It wasn't until the latter half of the twentieth century when schools were seen as organizations in their own right and studies of school climate emerged (Chirkina & Khavenson, 2018). As a result, the first school climate instruments were modified versions of organizational instruments,

with most focused on the practices, perceptions, and relationships among administrators, principals, and teachers (Chirkina & Khavenson, 2018; Halpin & Croft, 1963).

From 1960 to 1990, the breadth and depth of the school climate construct expanded, and its popularity swelled. Research now addressed student and family traits, school characteristics, and issues at the classroom and teacher level (Chirking & Khavenson, 2018; Coleman et al., 1966; Coleman et al., 1982; Kreft, 1993; Zullig et al., 2010). Over the past 30 years, the body of school climate research has continued to grow and unearth a plethora of subsequent benefits for schools and those within them (Thapa et al., 2012).

As school climate has gained popularity among educational researchers, the definition and operationalization of the construct have undergone a disjointed evolution across organizations and researchers (Anderson, 1982; Chirkina & Khavenson, 2018; Cohen et al., 2009; Halpin & Croft, 1963; Moos, 1979; Tagiuri, 1968; Zullig et al., 2010). However, years of research have provided a generalized understanding of how school climate can be defined and thus, measured. The current study defines school climate as a school's personality that reflects the collective perceptions of school members such as teachers, students, and parents (Hoy & Miskel, 2013). The norms, values, interpersonal relationships, teaching and learning practices, and adopted organizational structures within a school guide these perceptions (Thapa et al., 2012). Typically, these components cluster into five general domains: safety, relationships, teaching, learning, and external environment (Thapa et al., 2012; Van Eck et al., 2017).

The safety domain can pertain to physical and socio-economic safety issues within a school such as plans in place for addressing violent behavior, whether

individuals feel physically safe from harm, conflict resolution efforts, and the approach towards aggressive behavior such as bullying (Zullig & Matthews, 2014). For relationships, student-teacher, teacher-teacher, student-administrator, and teacher-administrator relationships can all contribute to a school's climate. Research has shown student-teacher relationships to be the most important, as teachers can provide students with emotional security and a set of values that can prompt increased student engagement and improved behavior (Pianta,1999; Zullig & Matthews, 2014).

The domains of teaching and learning often go hand-in-hand, as effective teaching strategies typically encourage student interest and engagement in learning. When teaching and learning consist of quality and creative instruction as well as lessons in appropriate social behavior, emotional regulation, leadership, and professional development, students feel better prepared to tackle academic and non-academic challenges within a school setting (Beghetto, 2006; Ghaith, 2003; Wentzel & Watkins, 2002; Zullig & Matthews, 2014).

Finally, the external or physical environment of a school is considered to be an important contributor to school climate. This dimension consists of elements such as cleanliness, school/classroom size, adequate learning materials, and activity space for extracurriculars such as theatre or sports (Conroy & Fox, 1994; McNeely et al., 2002; Mok & Flynn, 1997; Zullig & Matthews, 2014). It follows that schools with spaces designed to foster student engagement can facilitate a positive school climate.

The benefits of positive school climate are well-documented and have been a focal point of educational policy and reform for the past three decades (Thapa et al., 2012). Favorable school climate is associated with improved student academic

achievement (Greenberg, 2004; Lee & Burkham,1996; Stewart 2008), increased teacher job satisfaction (Ma & MacMillan, 1999), and enhanced home-school relationships (DiStefano et al., 2007). Additionally, the manageable nature of school climate compared to other barriers to academic achievement (e.g., school poverty levels) makes it a popular target of school reform initiatives among policymakers and researchers.

The purported benefits of improved school climate allowed for its inclusion as a school accountability measure. Signed into law in 2015, the Every Student Succeeds Act (ESSA) replaces No Child Left Behind (NCLB) and gives states more freedom in selecting accountability goals and systems. However, states are required to include a minimum of one non-academic indicator of school quality to measure improvements in areas such as school equity and climate (Penuel et al., 2016). Possible indicators include college and career readiness, chronic absenteeism and attendance, subject proficiency and progress (e.g., science, social studies), art access and participation, and school climate (Woods, 2018).

In 2018, only nine states planned to use school climate or engagement as an ESSA indicator of school quality or student success: Idaho, Illinois, Iowa, Maryland, Montana, Nevada, New Mexico, North Dakota, and South Carolina. (Woods, 2018). Nevada stopped using climate as an indicator in 2019 and, as of 2020, awarded points based on chronic absenteeism, academic learning plans and credit requirements. It appears as though Montana is still planning to implement a survey, but one has not been created or administered as of September 2021. In the 2020-2021 school year, South Carolina replaced their ESSA indicator, a student engagement survey, with a measure for chronic absenteeism (SC DE, EOC 2020).

Apart from the aforementioned states, five states currently administer school climate surveys under ESSA and publicly report them or require their use in struggling schools but do not use them as an accountability measure (see Table 2.1; Jordan & Hamilton, 2020). As of 2020, several other states and Washington, DC were piloting or examining the future use of school climate surveys for improvement or accountability (Jordan & Hamilton, 2020).

Table 2.1 *Current Applications of School Climate Surveys*

Climate Survey Applications	Count	States/Districts
Accountability	7	Idaho, Illinois, Iowa, Maryland, Montana, New Mexico, North Dakota
ESSA	5	California, Delaware, Georgia, Massachusetts, Nevada
Piloting/Studying	4	Indiana, New York, Ohio, Washington, DC

Among the remaining eight states that continue to include a school climate indicator as an accountability measure in their ESSA plan, the definition and operationalization of the construct may still vary. For example, North Dakota chose to focus on engagement (cognitive, behavioral, and emotional engagement as defined by Cognia), whereas states like Illinois define a much broader scope for school climate and how it will be measured. Jordan and Hamilton (2020) found that the most states include engagement as a topic in school climate surveys, followed by bullying, and physical and emotional safety. Academic expectations and rigor, positive relationships, equity and cultural respect, discipline and order, and health (mental/physical) were also common (Jordan & Hamilton, 2020). Table 2.2 provides more detail as to the differences in how

school climate/engagement is operationalized to meet ESSA accountability standards across these seven states.

From a measurement perspective, the diverse range of operationalizations seen in the above table can provide collectively rich conceptualization of school climate. However, it does make it more difficult to regulate the construct. The National School Climate Standards were developed by the National School Climate Council (NSCC) in an attempt to somewhat standardize the construct and to support schools in their climate improvement efforts (Ciccone & Freiburg, 2013). These standards provide a framework and criteria to help schools identify and support their vision of a positive school climate through improved policy and practice (see NSCC, 2007 for complete list). Educational researchers can model their instruments after these guidelines, while schools and educational leaders can use them to improve climate while informing state and federal accountability measures (NSCC, 2007).

However, while these standards may be useful for schools, their use is not required. States can choose if and how they will incorporate school climate into their accountability measures. There is also no set of national benchmarks or what constitutes effective improvement processes, policies, or practices (Carter, 2010; Cohen, 2014). This lack of cohesiveness in educational policies and accountability systems is made worse by the fact that most policies and systems are focused on academic achievement over issues of school climate and related issues (e.g., pro-social learning, professional development) (Cohen, 2014).

Table 2.2 *School Quality or Student Success Accountability Measures by State*

State	Weight	Report Card Inclusion	Grade Levels	Content	Survey Title / Company	Notes	Sources
Idaho	10%	Yes (not public)	K-8	Behavioral, cognitive, and emotional engagement	Cognia Student Engagement Survey	Grades 9-12 surveyed, but not included for accountability	Cognia (2020), Idaho State Department of Education (2019a, 2019b, 2021)
Illinois	5%	Yes	PK-12	Effective leadership, teacher collaboration, family involvement, environmental supports, and ambitious instruction	University of Chicago 5Essentials Survey (Cognia and Comprehensive School Climate Services alternatives available)	Responses for students in Grades 4-12 and teachers for Grades PK-12 are averaged to reach final score.	Illinois State Board of Education (2019, 2021a, 2021b), Jordan & Hamilton (2020)

State	Weight	Report Card Inclusion	Grade Levels	Content	Survey Title / Company	Notes	Sources
Iowa	18% (ES, MS) 8% (HS)	Yes	3-12	Physical and emotional safety, adult-student relationships, student-student relationships, diversity, environment expectations, and physical environment	Iowa Youth Survey: Conditions for Learning	Survey results are not overtly presented on report card but available via data download.	Iowa Department of Education (2018, 2020, 2021)
Maryland	10%	Yes	5-11	Safety, environment, community, and relationships	Maryland School Survey	Student and teacher results are combined and weighted (7% and 3% of the 10% for students and	Kautz et al. (2020), Maryland State Department of Education (2018, 2021)

State	Weight	Report Card Inclusion	Grade Levels	Content	Survey Title / Company	Notes	Sources
						teachers, respectively)	
Montana	5%	N/A	K-12	School climate, reducing behavior issues, and increasing	Not yet developed		Montana Office of Public Instruction (2018, 2020, 2021a, 2021b)
New Mexico	10 % (ES, MS) 5% (HS)	Yes	K-12	Learning experiences, access to educational resources, and learning conditions	Opportunity to Learn Survey	First administered in Spring 2019. Full points awarded when school's average score is 45/50. Students and parents surveyed.	New Mexico Public Education Department (2019, 2020, 2021)

State	Weight	Report Card Inclusion	Grade Levels	Content	Survey Title / Company	Notes	Sources
						Parents are surveyed for grades K-2, while students are surveyed for grades 3-12.	

Note. The findings presented in this table may be limited by the availability of updated information on each state's department of education website as of September 2021.

To refocus on climate, the characteristics of an effective school climate improvement process must be clearly delineated and differentiated from other school practices (e.g., positive behavioral interventions and supports; Cohen, 2014). Further, educational policies and accountability systems must be designed in a way that supports school climate reform (Cohen, 2014).

South Carolina School Climate

South Carolina has (SC) historically used school climate as an accountability measure for ESSA. In 2019, SC replaced this measure with one that centers on students' cognitive, behavioral, and emotional engagement (i.e., the Cognia Survey). This measure was abandoned for the 2020-2021 school year and was not replaced by a different survey due to limitations stemming from the Covid-19 pandemic. As a result, student engagement was assessed by using a federally-defined measure of chronic absenteeism that was not included in the state's accountability rating (SC DE, EOC 2020). However, the original school climate survey is still administered in all public schools to gauge yearly progress and inform future climate-based decisions. It is also possible that the instrument will be re-adopted as an ESSA accountability measure in the future. The 2018 school climate survey will be analyzed in the current study.

In the SC school climate survey, students, teachers, and parents are surveyed to assess schools' respective school climate performance. Students' perceptions of school climate are measured across 51 items and four dimensions: learning environment, social-physical environment, home-school relations, and safety. School climate for teachers is measured across 81 items and six factors including working conditions/leadership, home-school relations, instructional focus, resources, physical environment, and safety. Parents

are evaluated using 41 items, 21 of which are used for analysis and categorized under the domains of learning environment, social-physical environment, teacher care and support, or home-school relations. While surveys exist for each of these participant groups, the focus of the current study is on student school climate (reported information and data requests for teacher and parent perceptions of school climate are available through the SC Department of Education webpage). A list of all survey items and domains is provided in Appendix A.

Even though students, teachers, and parents in every SC public school receive an extensive school climate survey, only six items are included in the state's annual school report card. Of these items, only three measure students' perceptions of school climate. In the SC report card, schools are rated based on their performance on a number of indicators, specifically academic achievement, student progress, preparing for success, student engagement, English learners' proficiency progress, graduation rate, and college/career readiness. School climate items are reported as indicators for student engagement and student safety but do not contribute to a school's rating. A list of these survey items is provided in Table 2.3.

Apart from use in the state's district and school report card, data from the school climate surveys are evaluated each year by the South Carolina Education Policy Center at the University of South Carolina. Profiles of schools are created and discussed with school and district leaders to aid their understanding of yearly progress and their position relative to similar schools in the state and their respective districts. These meetings have proven to be an invaluable resource in helping administrators track their progress and locate areas where greater focus is needed.

Table 2.3 *South Carolina School Climate Items by Category and Group*

Survey Category	Survey Group	Survey Item
Student Safety	T	"I feel safe at my school before and after hours."
	T	"The rules for behavior are enforced at my school."
	P	"My child feels safe at school."
	P	"My child's teachers and school staff prevent or stop bullying at school."
Student Engagement	S, T, P	"I am satisfied with my school's learning environment."
	S, T, P	"I am satisfied with my school's social and physical environment."
	S, T, P	"I am satisfied with home-school relations at my school."

Note. Student = S, Teacher = T, Parent = P.

Measuring School Climate

As discussed in the previous section, there is currently no universal definition for or operationalization of the construct of school climate. And even if the opposite was true, the manner in which researchers choose to measure school climate can still vary. A wide selection of methodologies exists and can be used to evaluate a construct. In the case of school climate, however, the range of methodologies used to investigate climate has been rather narrow, with most studies opting to use variable-centered rather than person-centered approaches.

A variable-centered approach focuses on the relationships among variables (Laursen & Hoff, 2006). A strength of this approach lies in its parsimony (Howard & Hoffman, 2017). Individuals within the sample are assumed to belong to a single, homogenous population with respect to how predictor variables function in relation to the outcome variables (Laursen & Hoff, 2006). As a result, the approach yields a single set of

averaged parameters that can be readily interpreted (Howard & Hoffman, 2018; Morin et al., 2018).

The variable-centered approach can be contrasted with the person-centered approach. Person-oriented methodologies gather information about individuals based on the relationships between variables (Masyn, 2013). The person-centered approach allows for the identification of unobserved subgroups of individuals characterized by their responses on a given instrument—focusing on different classes/profiles of people or institutions rather than similarities between variables (Meeusen et al., 2018).

Factor analysis is an example of a variable-centered approach. A search of peer-reviewed journals for the terms "school climate" and "factor analysis" within the abstract returned 205 results published between 1987 and 2019 (Search was conducted on 12/30/2019 across 109 databases listed in Appendix B). Similar searches for person-centered approaches (i.e., latent profile, latent class, mixture models, cluster analysis) returned comparatively limited results. This finding appears to reflect practice where factor analysis, a variable-centered approach, serves as the most popular method for analyzing school climate. The search results for variable- and person-centered approaches are provided in Table 2.4.

Another methodological consideration is the data structure. Data used in educational research is typically nested in nature, meaning that data from individuals (e.g., students, teachers) are clustered within larger groups such as classes, schools, or districts. However, many school climate researchers neglect to include a multilevel component in their analysis to accommodate the nested data structure. Nested data creates statistical dependencies among individual observations, making observations

within a given group more alike than those outside that group (Aarts et al., 2014). This violates the independence assumption for observations (see section on LPA model assumptions for explanation). With variable-centered methodologies, consequences of violating this assumption include biased parameter estimates and standard errors as well as reduced statistical power (Bliese & Hanges, 2004; Kenny & Judd, 1986). Incorrect inferences may also result due to an invalid factor structure, suggesting that findings at one level hold at another level (e.g., that effects found at the student level also apply at the school level) (Diya et al., 2014).

Table 2.4 *Frequency of School Climate Methods by Type*

Method	Type	Counts	
		General (Date Range)	Multilevel (Date Range)
Factor Analysis	Item-Centered	205 (1987-2019)	6 (2002-2019)
Latent Class	Person-Centered	8 (2013-2019)	1 (2016)
Latent Profile	Person-Centered	2 (2015-2018)	1 (2017)
Cluster Analysis	Person-Centered	7 (2004-2019)	0 (N/A)
Mixture Model	Person-Centered	1 (2012)	0 (N/A)

Note. The results presented in this table are confined by the limitations set by the search procedure and is meant to provide a generalized finding. The general count (date range) refers to the number of articles retrieved and the dates they were published.

Considering person-oriented methods, this violation can prompt biased classification error estimates, incorrect profile sizes, inaccurate posterior classification of cases, and overall model misfit that can provoke researchers to select more profiles than necessary (Albert & Dodd, 2004; Mclachlan & Peel, 2000; Torrance-Rynard & Walter, 1998; Vacek, 1985, as cited in Oberski & Vermunt, 2018). Thus, the failure to account

for nested data in both variable- and person-centered approaches can prove seriously detrimental to producing trustworthy results and arriving at accurate conclusions as it relates to practices and policy decisions involving school climate.

While multilevel models are very important in helping researchers make valid statistical inferences when working with nested data, the level of their implementation is wanting. A search of the literature suggests that the vast majority of multilevel research on school climate was published within the last 20 years. A search of abstracts from peer-reviewed works published in the last 20 years located 7,770 abstracts with the phrase "school climate" and 762 abstracts with the terms "school climate" and "multilevel." Thus, it is possible that only 9.8% of school climate articles within the searched databases incorporated a multilevel dimension.[2]

The absence of including both multilevel and person-centered approaches in studying school climate is noteworthy. The nested nature of school climate data necessitates the use of a multilevel model for statistically sound inference. Unlike the variable-centered approach, the person-centered approach operates under the assumption that a "population is heterogenous with respect to how predictors operate on the outcomes" (Laursen & Hoff, 2006, p.379). Thus, the research questions involved in person- and variable-centered procedures are inherently different and can provide a distinctive glimpse into construct of school climate.

The scarcity of person-centered work on school climate limits our view of what school climate is and how it currently operates within and across schools. In a database

[2] Note that the exclusion of the term "multilevel" from a search did not preclude multilevel studies from being listed within the search results for school climate.

search for peer-reviewed works that incorporate both a person-centered (i.e., latent profile, latent class, mixture, cluster analysis) and multilevel approach, results were sparse. Looking again to Table 2.4, the added dimension of multilevel analysis reduced the number of returned studies for cluster analysis from seven to zero. Latent profile and latent class search results fell from two and eight findings to one, respectively. Cluster analysis fell from one finding to zero findings. If these findings are in any way indicative of the current pool of research on school climate involving person-centered and multilevel approaches, then a serious gap exists in the school climate literature on a global scale.

Measuring Climate in South Carolina

In many ways, the research conducted on school climate surveys used in South Carolina reflect the findings at the (inter)national level. At present, the relative performance of SC schools on the climate surveys is determined using a single-level, variable-centered approach—factor analysis. The SC report cards also adopt an item-centered approach and provide an arguably over-simplified average response for each item for each school.

While other research has been conducted on the SC school surveys that is multilevel or person-centered in nature (see Chapter 2 for more details), this research has not been integrated into practice at the school, district, or state level. The example of South Carolina is a perfect reflection of the current state of affairs as it relates to school climate research wherein a sizeable gap exists between school climate research findings and policy, school improvement practices, and teacher professional development (Cohen et al., 2009).

In using factor analysis to analyze SC school climate data, the nesting of students within schools has not (to date) been considered when evaluating the factor structure for the state's school climate survey. Factor scores are computed and compared across schools on the measured domains, adjusting for school level and poverty. The domains of school climate measured in the SC student survey include learning environment, social-physical environment, home-school relations, and safety. Teachers domains include working conditions/leadership, home-school relations, instructional focus, resources, physical environment and safety. Parents are evaluated using across domains of learning environment, social-physical environment, teacher care and support, and home-school relations. Poverty is typically measured by the percent of students eligible for free or reduced-price meals (FRPL), though some hold that recent expansions in access to FRPL have diminished its utility as a proxy for poverty and pushed states to use different indicators (Grich, 2018).

The aforementioned factor scores are also based on individual-level responses that are combined to represent an overall view of a school's performance on climate subdomains. In other words, one can see how a school performs on average for each domain and overall. While this can be helpful in tracking SC schools' general progress over time, a detailed view of the heterogenous groups that contribute to this average is lacking. A person-centered approach when combined with a multilevel approach can resolve this issue. Not only can it provide greater insight into school climate at the ground-level, but taking into consideration the school level structure may help policy-makers avoid critical errors that may feed into daily practices and policy decisions.

As previously stated, the SC school surveys have been evaluated using either multilevel or person-centered procedures, but never both. The current study aims to address this gap by conducting a multilevel latent profile analysis (MLPA) to evaluate school climate within South Carolina. In doing so, the current study will also contribute to the shortage of school climate research involving a person-centered, multilevel approach. The following section examines characteristics of the adopted methodologies within the current study. Core concepts and applications of person-centered approaches, LPA, and MLPA are discussed at length. The concluding section at the end of this chapter highlights the role of the current study in relation to scholarly literature on school climate and MLPA.

Method Details and Applications

Person-Centered Approaches

Person-centered approaches are relatively uncommon in the study of school climate compared to item-centered methodologies. However, person-centered approaches provide a unique and detailed look into the construct that focuses on the relationships among individuals rather than between items. One goal of this approach is to identify unobserved subpopulations/subgroups of individuals that are marked by different relationships across parameters so that individuals within a grouping are more alike than those between groupings (Jung & Wickrama, 2008; Meyer & Morin, 2016). Another is to better understand the relationships between identified subgroups and a selection of predictors, correlates, and/or outcomes (Howard & Hoffman, 2017).

These aims are guided by the assumption that all individuals within a sample originate from a heterogenous population. Such diversity within a population prevents the

use of a single set of population parameters and necessitates the production of multiple parameter sets to provide a more detailed picture of the subpopulations within the sample (Collins & Lanza, 2013; Howard & Hoffman, 2017; McCutcheon, 1987). This differs from the item-centered approach which assumes that all individuals belong to a single population, allowing a solitary set of averaged parameters to be estimated (Meyer & Morin, 2016).

In effect, a person-centered approach provides a more finely-tuned strategy for examining a construct than one that is item-centered. Not only are individuals treated more holistically by focusing on variable patterns over comparisons to averages on solitary variables, but consideration of patterns across the set of variables may promote the discovery of important and complex interactions among variables that could otherwise be ambiguous or go undetected (Meyer & Morin, 2016). According to Bauer and Shanahan (2007), the location of emergent and evolving interactions poses a significant methodological challenge that could be addressed through person-centered methodologies.

Examples of person-centered approaches include latent profile analysis (LPA), latent class analysis (LCA), and cluster analysis. Cluster analysis differs from LCA and LPA in that it is a computational learning method where groups of observations or individuals are defined by an arbitrary distance measure (e.g., Euclidean distance). In contrast, groups of individuals in LCA and LPA are determined using a probabilistic model that allows for more flexibility in its specification, the inclusion of variables with varying scales, and the incorporation of both continuous and categorical variables within

the analysis (Everitt, 1993; Institute of Medicine, 2014; Marsh et al., 2009; Morgan, 2015; Tryfos, 1998).

Assumptions can also be relaxed in terms of allowing parameters to be estimated or restricted (i.e., free or fixed), classification uncertainty is permitted (e.g., cases can have unique probabilities of belonging to each profile), and covariates and outcome variables can be incorporated into a model-based approach, further enhancing model flexibility (Bandeen-Roche et al., 1997; Collins & Lanza, 2010; Dayton & Macready, 1988; Lanza et al., 2013; Morgan, 2015). Model-based approaches also allow for the use of fit indices to compare multiple models and make more informed decisions about the number and makeup of resulting subgroups (Marsh et al., 2009).

Both LCA and LPA share a modeling framework and are classified as finite mixture models. Finite mixture models (FMMs) are named as such because they express a general population distribution as a finite mixture of a certain number of unknown components (Masyn, 2013). These models are colloquially known as ‘mixture models’ and are discussed in the following section. Despite this shared framework, the representation of observational data differs across LPA and LCA. Data is classified as categorical when using LCA, while LPA adopts a continuous classification of observations. Because the current paper is focused on LPA methods, the remainder of this paper will only use the term LPA when discussing the concepts and procedures for this study, though much of what is discussed may also apply to LCA procedures.

Mixture Modeling: Core Concepts & History

In educational and statistical research, it is often assumed that sample data originates from a homogenous population in which members of said population perform

similarly on a construct of interest. This assumption and the subsequent pooling of data across respondents is often deemed to be an unsound decision in the behavioral and social sciences, as subgroups or subpopulations of individuals can cluster together as a result of one or more variables and create population heterogeneity (Muthén, 1989; Jedidi et al., 1997). If such heterogeneity is overlooked, subsequent results can paint an inaccurate picture of the population of interest.

To better understand the concept of population heterogeneity, consider the following simplistic example. Imagine a group of 20 ninth grade students who have taken a diagnostic Spanish exam at the beginning of the year to gauge their understanding of the subject. The instructor plans to use this information to create his lesson plans. When the instructor averages the scores of his students, he notes an average score of 80/100 points (80%). Elated that his students have retained so much knowledge over the summer, he creates a more rigorous lesson plan. However, while the instructor assumed that the class would understand most of the material, he failed to recognize that his classroom may actually be composed of different groups of students. In reality, there are two distinct groups: one group composed of students who were severely unfamiliar with Spanish and another group of students who had taken a Spanish immersion class over the summer break. Of course, the group of students who had practiced their language skills over the summer would increase the average class score. If the instructor ignores the possibility that the average score does not represent the entire class of students, then the lesson plans will not meet the needs of all of his students.

As illustrated by the above example, population heterogeneity can be observed or unobserved. Observed heterogeneity involves individuals who are knowingly assigned to

specific groups, such as the control and experimental groups in an experimental design study (Lubke & Muthén, 2005). If the instructor had divided his class before summer break into two groups, with and without a Spanish immersion class, then he would have known how to cater the lesson plans to each group. However, with unobserved heterogeneity, individual membership to various subpopulations is unknown as are the variables contributing to the emergence of these subpopulations (Lubke & Muthén, 2005). Estimated parameters (e.g., mean class score) will then fail to reflect the parameters of each subpopulation (e.g., non-immersion, immersion), as was illustrated by the illustrated example (Jedidi et al., 1997).

Variables that are not directly observed are called latent variables. Because they are unobservable constructs, they can only be measured or explained by proxy—in other words, by an observable indicator that is often accompanied by measurement error (McCutcheon, 1987). They can also be conceptualized as being categorical or continuous in nature and evaluated using a host of methods from factor analysis to mixture modeling. Ultimately, the concept of latent variables proves very useful in the case of unobserved heterogeneity and in the detection of important subpopulations that may improve one's understanding of important theoretical constructs such as school climate.

Mixture models are latent variable models that are used to detect unobserved subgroups, or mixtures of individuals (Lubke, 2010). Many types of models exist within the mixture modeling framework including, but not limited to, latent class analysis (LCA) and latent profile analysis (LPA) (Masyn, 2013). Regardless of the model type, mixture models express the overall population distribution as a finite mixture of some number of

unknown groups or components (Masyn, 2013). For this reason, LPA and LCA are often referred to as finite mixture models.

The evolution of finite mixture modeling begins with Karl Pearson's (1894) examination of two subspecies of crab using the method-of-moments approach and his discovery of two normally distributed mixing components, or two crab subspecies (Masyn, 2013; McLachlan & Peel, 2000). In 1972, Tan and Chang moved beyond the labor-intensive method-of-moment approach and onto the maximum-likelihood approach. Dempster et al. (1977) advanced this approach using the estimation-maximization (EM) algorithm, allowing the maximum likelihood (ML) estimation of incomplete data (Masyn, 2013; see section on LPA Model Estimation for more details on the EM algorithm and ML estimation).

In a related, albeit separate, timeline from finite mixture modeling, latent class models (LCMs) began their evolution after Spearman's (1904) factor analytic work that framed latent variables as categorical in nature (Masyn, 2013). Seminal research by Lazarsfeld and Henry (1968) propelled latent class modeling forward via the examination of latent attitudinal variables from dichotomous survey items (Magidson & Vermunt, 2004; Maysn, 2013; McCutcheon, 1987). At the time, the model designed by Lazarsfeld was called a latent structure model (LSM) and was often limited to examining dichotomous manifest/indicator variables and a single categorical latent variable (Goodman, 2002). It also lacked a general, reliable, and widely-implemented estimation method for obtaining parameter estimates (Goodman, 2002; Masyn, 2013).

Latent class models took a leap forward in the 1970s and were generalized to address the limitations of the older LSMs (Goodman, 2002). Work by Goodman (1974)

allowed for newer LCMs to be applied to polytomous as well as dichotomous observed variables, include more than one latent variable, and accommodate various model parameter constraints (Goodman, 2002). Clogg (1977) was the first to incorporate the techniques into readily available software (Masyn, 2013). This paved the way for the discovery that Goodman's (1974) approach was related to the estimation-maximization algorithm by Dempster et al. (1977), allowing for further advancement of estimation methods for obtaining parameter estimates (Masyn, 2013).

Advancements in statistical computing and popular use of the EM algorithm have both contributed towards the accelerated development, extension, and application of latent class and finite mixture models; they have also highlighted the overlap between both model types (Masyn, 2013). This is why, while mixture models and latent class models evolved separately of each other, latent class models (e.g., LPA, LCA) are now often perceived as falling underneath the general finite mixture modeling umbrella. The next section will explore Latent Profile Analysis (LPA) in more detail for use in the present study.

Latent Profile Analysis

Latent profile analysis has several broad characteristics that separate it from other latent class methodologies. The recovery of unobserved subgroups is based on the means of continuous observed variables, similar to factor analysis (Oberski, 2016). Latent profile analysis and item response theory (IRT) look at the means of categorical/discrete observed variables (Oberski, 2016; Wagner et al., 2010). However, both LPA and LCA identify the latent variable as discrete, while factor analysis and IRT use a continuous latent variable (Oberski, 2016).

Another feature of LPA is that is a person-centered approach. As previously discussed, a person-centered approach seeks to gather information about *individuals* based on the relationships between variables (Masyn, 2013). This can be contrasted to a variable-centered approach, where the focus is on the relationships *among variables* and these variable relationships are assumed to hold for all individuals within a population (Masyn, 2013; Laursen & Hoff, 2006).

LPA Model Assumptions. The LPA is a probabilistic model, meaning that it models the probability of an observation belonging to any given profile. Probabilistic parameterization is characterized by observed indicator variables, latent variables, latent class probabilities, and conditional probabilities (McCutcheon, 2002a). It assumes that any two manifest variables are locally independent, meaning that the latent variable explains any relationships between them (Magidson & Vermunt, 2004; McCutcheon, 1987, 2002a). This is often referred to the axiom of local independence or the local independence assumption (Heinen, 1996; Lazarsfeld & Henry, 1968; McCutcheon, 2002a). For LPA, this means that indicators are uncorrelated, given latent profile membership (though, this assumption can be relaxed and allow the free correlation of indicators within profiles) (Nylund-Gibson & Choi, 2018). Other assumptions of latent profile models are that each observation (i.e., individual) belongs to only one latent profile and that that indicators follow a given distribution (e.g. normal, non-normal) within each profile (Hickendorff et al., 2018; Magidson & Vermunt, 2004; Oberski, 2016).

LPA Model and Parameters. The current study's presentation of the LPA model and its parameters is modeled after the specification guidelines set forth by Masyn

(2013). In an LPA model, there are M continuous latent class indicators, $y_i, y_2, \dots, y_M$ and n participants. The observed response to a given indicator, m, for participant i is represented by y_{mi}. The categorical latent variable, c, has K classes, where $c_i = k$ if individual i belongs to class k. The symbol π_k denotes the proportion of individuals in Class k. Each individual may only belong to one of the K classes, and the sum of the proportions of individuals within each class sums to one ($\sum \pi_k = 1$).

Equation 1 depicts the relationship between observed responses and the latent class variable in an unconditional LPA model. The y_i represents the vector of observed responses for a given participant, $y_i = (y_{1i}, \dots, y_{Mi})$. The multivariate probability density function for the overall population is represented by $f(y_i)$, and the class-specific density function for Class k is represented by $f_k(y_i) = f(y_i | c_i = k)$. This model specifies that the overall joint distribution of the M continuous indicators is the result of a mixing of K component distributions of the M indicators, with $f_k(y_i)$ representing the component-specific joint distribution for y_i.

$$f(y_i) = \sum_{k=1}^{K} \pi_k \cdot f_k(y_i) \tag{1}$$

LPA models are composed of both structural and measurement parameters. Structural parameters correspond to the distribution of the latent class variable. They are essential profile proportions (π_k) and should sum to one. For example, within a sample, .30 of observations belong to Profile A, while .50 and .20 of observations belong to Profiles B and C, respectively (Hickendorff et al., 2018). Measurement parameters in LPA are related to the class-specific probability distributions and consist of class-specific indicator means, variance, and covariance (Masyn, 2013).

The within-class distribution of the continuous indicator variables is usually assumed to be multivariate normal (see Equation. 2). In Equation 2, α_k represents the vector of Class k means for all individuals (i.e., $E(y_{i|k}) = \alpha_k$), while Σ_k is the Class k covariance matrix for those individuals (i.e., $Var(y_{i|k}) = \Sigma_k$).

$$[y_i|c_i = k] \sim MVN(\alpha_k, \Sigma_k) \tag{2}$$

While a parametric distribution is assumed to exist within each class, no assumptions are made with regard to the joint distribution of indicators in the population. Within-class variability and the mean structure of indicators are permitted to vary across profiles. Class-specific estimates of means, variances, and covariances can also be uniquely identified for each class, as long as within-class distributions are assumed to be normal (Masyn, 2013).

LPA Model Estimation. The purpose of model estimation is to estimate the parameters of interest. The most popular method of estimation for is the Expectation-Maximization (EM) algorithm. This method uses a maximum likelihood estimation (MLE) technique in an iterative approach.

The MLE process begins with the likelihood function for the complete set of data (Masyn, 2013). The likelihood function is defined as the probability density of all the data given a set of parameter values; and when these values are maximized with respect to those parameters, the result is the maximum likelihood estimates of those parameters (Masyn, 2013). In the case of latent profile analysis, maximum likelihood estimates are the values of the class-specific means, variances, and covariances (i.e., the parameters) that maximize the likelihood of the data in your sample (Masyn, 2013; McCutcheon, 1987).

The complete data likelihood for a given individual (i) and a missing latent class variable (c_i) is illustrated in Equation 3, where the vector of the unknown parameters to be estimated is represented by Θ (Masyn, 2013). The product of the individual likelihoods in Equation 3 yields the likelihood function for the entire sample (L). The use of this function requires that all observations be considered as independent of one another (Masyn, 2013). The natural log of the function is then taken to facilitate the ease of maximization, as shown in Equation 4 (Masyn, 2013). The natural log is a monotonically increasing function, meaning that over a given interval, it is only increasing, and the first derivative of the function is always positive (Masyn, 2013; Bergonio, 2013). Once the first derivative of the function within a given interval becomes zero, or undefined, it is likely at a local or global maximum of the function (Bergonio, 2013). This means that the parameter values (Θ) that maximize the log likelihood function are indeed the maximum likelihood estimates $(\widehat{\Theta}_{\mathrm{ML}})$ (Masyn, 2013).

$$l_i(\Theta) = \Pr(y_i, c_i|\Theta) = \Pr(y_i|c_i, \Theta) \cdot \Pr(y_i|\Theta) \tag{3}$$

$$ln\left(\prod l_i(\Theta)\right) = \ln\big(L(\Theta)\big) = LL(\Theta) \tag{4}$$

In the discussion involving Equation 3, it was mentioned that the latent class variable (c_i) was missing. The reason for this missingness is that latent classes are unknown. In latent variable/ mixture modeling, because these latent groups are unknown, we can treat them as missing in the model (Muthén, 2001). This missingness complicates the computation of MLEs because there is no closed-form solution (Bishop, 2006; Masyn, 2013). For this reason, an iterative approach must be adopted (Bishop, 2006; Bishop & Nabney, 2008; Fletcher, 1987; Masyn, 2013; Nocedal & Wright, 2006).

The EM algorithm is one such iterative approach. Developed by Dempster et al. (1977), the EM algorithm was presented as an iterative, maximum likelihood estimation approach using incomplete data where the missing data were the latent profile/class assignments for individual observations (Masyn, 2013; McCutcheon, 2002a). While other algorithms exist and have certain advantages (e.g., Newton-Raphson), the EM algorithm is the most widely used and available in modern statistical programs and was therefore adopted in the current study.

The EM algorithm consists of two major steps—the expectation step and the maximization step. In the expectation step (E-step), the expected value of the log-likelihood function is computed based on the observed data and initial parameter estimates (Masyn, 2013). These expected values are also known as the posterior probabilities. A posterior probability is the probability or weight that a data point belongs to each component (e.g., group, profile).

The maximization step (M-step) follows wherein the function is maximized to yield new parameter estimates that replace the initial estimates. In other words, the posterior probabilities are used to re-estimate the model parameters for each component/profile. These two steps repeat the estimation and re-estimation of parameter estimates until a stopping criterion is met, and for this reason, the EM algorithm is considered to be an iterative approach (Masyn, 2013; McCutcheon, 2002a).

For the EM algorithm, one stopping criterion is the amount of change across the parameter estimates from one iteration to the next. When this amount becomes sufficiently small (i.e., converges on a value near zero), the iterative process stops (McCutcheon, 2002a). One could also specify a maximum number of iterations (Masyn,

2013). The goal in this case is to prevent the model from iterating for abnormally long periods of time, as it is possible that the algorithm lacks enough power to find a global maximum (Masyn, 2013).

A key characteristic of the log likelihood function that affects the convergence of the EM is the presence of various maxima. A likelihood function can have several local maxima, but only one global maximum. Akin to a mountain range, there may be many mountains, but only one can boast the highest elevation (Masyn, 2013). The tallest mountain within that range would be the global maximum, while the shorter mountains surrounding it would qualify as local maxima. Similarly, the surface of the likelihood function for a mixture model could have many local maxima, however, the identification of a global maximum is required for the model to converge (Lubke, 2010).

Unfortunately, the EM algorithm is incapable of distinguishing between a global and a local maximum. To prevent the function from converging on a local instead of a global maximum, different sets of random starting values should be used at the start of the estimation process (Lubke, 2010; Bartholomew & Knott, 1999). The maxima located for each starting point are compared and the one with the highest likelihood is considered to be the global maximum (Wang & Zhang, 2006).

However, if an EM algorithm fails to converge, a model may be weakly or under-identified, either theoretically or empirically (Masyn, 2013). Common culprits are multiple local maxima, saddle points, and regions that are almost flat across the log-likelihood surfaces of mixture models (Masyn, 2013). The use of multiple sets of starting values, an iterative procedure, and a high frequency of replications can alleviate these complications to some extent (Masyn, 2013). Identification is also closely related to

model precision, where increased precision can prompt unidentifiability (Bartholomew & Knott, 1999). For this reason, some researchers suggest limiting the model to having no more than three to four profiles/subgroups and collapsing response categories for indicator variables to reduce the number of class-specific indicator parameters to be estimated and increasing the ratio of 'known' to 'unknown' information in the model (Bartholomew & Knott, 1999; Masyn, 2013). Small sample size and a large number of variables can also contribute to convergence on a local rather than a global maximum in finite mixture models (Bartholomew & Knott, 1999; Wedel & DeSarbo, 1995).

To illustrate what has been discussed so far, consider the following LPA example with an application of the EM algorithm (adapted from Oberski, 2016). Imagine that data has been collected on respondent height. No other information on the sample is available, but the researchers believe that the data is actually composed of two separate distributions: male and female. Thus, the sample is believed to be a mixture model that contains a combination of multiple unknown probability distribution functions.

To address these unknowns, we assume that the probability curve for the latent variable (gender) is made up of the weighted sum of two normal curves, or: $p\ (height) = \pi_1^X Normal(\mu_1, \sigma_1) + (1 - \pi_1^X) Normal(\mu_2, \sigma_2)$. In this formula, X is a dummy variable that could be coded as "1" for male and "2" for female (or the reverse). Assuming normal distributions exist for the heights of male and female respondents, we can now try to find the means and standard deviations of these distributions for each profile (Obserski, 2016, p.4-6).

To start the modeling process, random starting values for the profile (male, female) means and standard deviations can be plugged into the model. Based on these

starting values, a posterior probability is computed for each individual using their actual height and the probability density of observing a person with that height. Recall that a posterior probability is the probability that each individual to belongs to each of the latent profiles. Thus, an individual with a height of 66 inches may have a .75 posterior probability of being female and a .25 posterior probability of being male. One then takes the product of each posterior probability and height and adds the resulting values to the female mean estimate (female estimate + .75*66) and the male mean estimate (male estimate + .25*66). This is repeated across all observations, and each person's observed height contributes a given percentage to one profile or the other, depending how strongly the data supports their being male or female (Oberski, 2016).

The amount of weight an individual contributes to a profile is proportional to the relative likelihood that the point was generated by that component (male, female). Thus, the conditional probability distribution permits the computation of the conditional expected log-likelihood and one's ability to determine which parameter estimate values maximize the function. This value serves as your new estimate and the process is repeated until the difference between the old and new estimates become largely indistinguishable (i.e., convergence) (Oberski, 2016).

If multiple maxima exist, the test can be repeated within specified value ranges and then compared to locate the global maximum. If this procedure works and exhibits good model fit under the assumption of two groups being present, then the resulting group probability assignments may be indicative of male and female respondents.

In sum, when the likelihood function converges on a (hopefully) global maximum, and the changes in parameter estimates from one iteration to the next becomes

sufficiently small (or, meet other stopping criterion), the algorithm provides model parameter estimates which are then used to assign individual observations to specific profiles based on their posterior probabilities (Jedidi et al., 1997; McLachlan, 1992). The final configurations of profiles will vary depending on the number of profiles one attempts to identify, their relative size, item quality when using the EM algorithm with LPA (McCutcheon, 1987). Model fit indices and criteria for the various configurations of profiles are evaluated to arrive at an appropriate model, as discussed in more detail in the following section.

LPA Model Building. Model building centers around the process of selecting the best model that represents the given data. In the case of latent profile modeling, this means determining how many profiles/subgroups may be present in your data. To do this, the model estimation procedures detailed in the previous section are repeated, each time allowing the formation of a different number of classes. The model fit statistics for each of these models are then analyzed and compared to determine the 'correct' number of profiles. The word 'correct' in this instance is a misnomer when dealing with empirical research, as one can never know with 100% accuracy whether the classification of observations is correct.

The steps of model building can also be referred to as the class enumeration process, as the central goal is to determine the correct number of profiles/subgroups/classes for your model. The first step in this process is to specify a one-class model and record the associated fit statistics, log-likelihood value, and number of estimated parameters. Once this step is completed, the number of classes is specified to increase by one and the same information is recorded. The process repeats until the

models are no longer well-identified (Masyn, 2013). The models believed to have the best fit or be most representative of the sample should then be selected for comparison using a combination of fit indices and other evaluative criteria.

Evaluating Model Fit

There are three main types of fit indices applied in the evaluation of latent class models: absolute fit indices, relative fit indices, and classification diagnostics (Masyn, 2013). These measures, as well as graphical evaluation methods (e.g., elbow plots) are discussed in detail below.

Absolute fit. Absolute fit indices evaluate the consistency of the model's representation of the data with the actual data itself (Masyn, 2013). In other words, it looks at the expectation of what the data should look like compared to its actual appearance.

A popular absolute fit index is the log likelihood difference test which gives information related to overall fit of a model to the data. However, it is not recommended for use in LPA. Inaccuracies in the resulting test statistics may occur because multiple distributions (and therefore, the test statistics) cannot be approximated when missing data in the form of non-response or missing profile information exists and creates 'holes' in the multiway contingency table (Nylund et al., 2007; Roesch et al., 2010). The index is also not recommended for comparing nested (or K vs. K-1) models, where K represents the number of profiles or groups. This is because the difference in chi-square values between the models (x^2_{diff}) lacks a chi-square distribution under the null hypothesis (Masyn, 2013; McLachlan & Peel, 2000).

Relative Fit. The second category of fit indices are designed to measure relative model fit. Relative fit indices only serve to compare the fit of one model to another so as to determine which model is 'better' in the eyes of the researcher. However, they do not identify whether either model has good fit or quantify the degree to which one model may be an improvement over another (Masyn, 2013).

Standardized residuals also aid in evaluating the comparative fit of two models. Using both model-estimated and observed pattern frequencies, the raw residual for each response pattern is computed and then standardized to create a standardized residual as shown in Equation 5, where the difference between the observed and predicted response pattern is represented by the numerator on the right side of the equation ($f_r - \hat{f}_r$) (Masyn, 2013). Response patterns with large values (e.g., $|std\hat{res}_r| > 3$) indicate poor fit and contribute the most to model rejection. The overall proportion of poor response values should also be evaluated to ensure that no more than 1-5% of response patterns exhibiting poor fit (Masyn, 2013).

$$std\hat{res}_r = \frac{f_r - \hat{f}_r}{\sqrt{\hat{f}_r\left(1 - \frac{\hat{f}_r}{n}\right)}} \tag{5}$$

The most commonly used relative fit indices in mixture modeling include the Bayesian Information Criterion (BIC; Schwarz, 1978), the adjusted BIC (aBIC, Sclove, 1987), the Consistent Akaike's Information Criterion (CAIC, Bozdogan, 1987), and the Approximate Weight Evidence Criterion (AWE; Banfield & Raferty, 1993) (Masyn, 2013). Each of these criteria consists of a goodness-of-fit term plus a penalty to control

for overfitting a model, and smaller values are indicative of better models (Dziak et al., 2012).

In addition to these indices, one may also analyze relative fit using non-inferential information criteria that allow you to quantify (to a degree) the relative performance of models (Masyn, 2013). Among them are the Bayes Factor (BF) and the approximate correct model probability (cmP). Both compare relative fit between models, but the BF is limited to two models whereas the cmP can compare more than two (Masyn, 2013). Thus, the cmP would yield the probability of a model being correct compared to multiple other models when equal weight is placed on the prior probabilities of the model; whereas the BF would yield the probability of a model being correct compared to another model (Masyn, 2013; Nagin, 1999).

The parametric bootstrapped likelihood ratio test (BLRT) and the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT; Lo et al., 2001) are also examples of relative fit indices. These tests are discussed further in the section on multilevel latent profile analysis.

Classification Diagnostics. The final category of fit indices is reserved for classification diagnostics. As the name suggests, classification diagnostics are designed to evaluate the precision of latent profile/class assignment for observations (Masyn, 2013). Two examples of classification diagnostics include average posterior class probability (AvePP; see Masyn, 2013) and the odds of correct classification ratio (OCC; Nagin, 2005; Masyn, 2013). Each of these is computed using posterior class probabilities which are defined as the "model-estimated values for each individual's probabilities of being in

each of the latent classes based on the maximum likelihood parameter estimates and the individual's observed response on indicator variables" (Masyn, 2013, p.569).

The AvePP, is the mean of the posterior class probabilities for all individuals within a given profile and indicates the level of classification uncertainty for each latent subgroup/profile/class (Masyn, 2013; Wong, 2019). The OCC is the odds of correct classification for an individual within a given class (Wong, 2019). Estimates of AvePP and OCC should be above 0.70 and above 0.5, respectively, to indicate adequate class separation and accurate profile assignments within a model (Masyn, 2013; Wong, 2019).

Entropy can also be used to evaluate the quality of latent class identification within a model. Larger values of entropy indicate clearer distinctions between latent classes, with values of entropy ranging from zero to one(Asparouhov & Muthèn, 2018). While entropy evaluates the quality of the entire measurement instrument, the quality or contribution of individual items within that model can also be evaluated using univariate entropy. Indicators with higher values of univariate entropy (within a range of zero to one) are considered to be more informative in identifying latent classes (Asparouhov & Muthèn, 2018).

Graphic representation of data can also be very useful during the class enumeration process. When relative fit indices (e.g., BIC, CAIC, AWE) are used, a 'better' model is one with a smaller value. However, no information criteria are guaranteed to arrive at a single lowest value and the smallest value may actually occur at the k_{max} class model, even though the resulting increase in model fit or information is practically insignificant (Masyn, 2013).

Elbow plots can be used to address this issue. Similar to a scree plot of eigenvalues in factor analysis, elbow plots graph values for the relative fit index (e.g, BIC) against the number of subgroups/classes (e.g., 1-K, where K is the maximum number of classes/subgroups). The idea is that as subgroups are incrementally added, the marginal gains of adding a subgroup will diminish and an angle (or elbow) will appear in the plot (Masyn, 2013). The location of the 'elbow' is an indicator of the 'correct' number of classes for the model.

Issues to Consider. When evaluating model fit, indices are to some degree reflective of the level of model parsimony. This means that models with the fewest number of classes/profiles and good model fit should be selected—prioritizing simplicity over minimal or insignificant increases in model fit. Thus, prioritizing parsimony over fit (or vice versa) is a decision to be made by the researcher and should be one that is strongly guided by theory (Hancock & Mueller, 2013).

Regardless of the how the 'best' model is selected, any model with unknown parameters and an unknown 'true' structure leaves room for error. Misspecification of the within-class components of a model (e.g., mean and covariance structures) can lead to spurious class/profile formations and an incorrectly determined final number of classes/profiles (Bauer, 2007; Hancock & Mueller, 2013). Bauer (2007) and Bauer and Curran (2004) also contended that classes may emerge as a result of using the wrong distributional form for the within-class model (e.g., assuming a normal distribution for a non-normal population distribution). It is possible that profiles may form as a result of the non-normality rather than the presence of two distinct subgroups of individuals (Hancock & Mueller, 2013). The linearity of exogenous covariates, whether data is considered to be

missing at random, and the independence of observations are also a concern (Bauer, 2007). Thus, latent profile models must be evaluated under the assumption that these errors are possible and that any identified classes may not be representative of true latent subgroups in the population of interest (Hancock & Mueller, 2013).

Finally, the ability to select the most appropriate model is also influenced by power which can aid in the detection of small classes as well as the discrimination between model alternatives (Lubke, 2010; Lubke & Neale, 2008). All of the aforementioned issues should be considered during the model building and evaluation processes to preserve the integrity of the resulting latent profiles to the best of one's ability. Further, these potential problems highlight the importance of presenting a selection of models rather than a single, best-fitting model to represent one's data (Lubke, 2010).

LPA and School Climate. A dearth of studies pertaining to the measurement of the school climate construct via standard LPA exist in the current peer-reviewed literature. A search for standard LPA applications for school climate returned varied results, but many applications covered topics related to school climate (e.g., bullying, environment, student engagement) rather than the overall construct. For example, Mindrila et al. (2018) conducted a standard LPA to develop latent profiles of student victimization, with school behavior management as a covariate and weapon carrying as a distal outcome (i.e., variable dependent on latent class membership). Lorenzo-Blanco et al. (2016) sought to create latent profiles of Latino/a youth based on their perceived diverse community experiences (discrimination, bullying, social support, and school

safety) and looked for associations between these profiles and prevalence of depressive symptoms, cigarette smoking, acculturation, and gender.

Other standard LPA applications that are somewhat related to school climate include one by Qahri-Saremi and Turel (2016) concerning student engagement and another by Gini et al. (2019) regarding cyber victimization. Two studies were also located involving creating latent profiles for teachers, focusing on their perceptions of student behavior and school environment (Pas & Bradshaw, 2014) and teacher stress (von Suchodoletz et al., 2019). Orpinas et al. (2014) created latent profiles for students based on teacher ratings of assets and maladaptive behaviors, later linking them with rates of school dropout. A study by Virtanen et al. (2019) analyzed latent profiles of psychological well-being for Finnish students as they transitioned from Grade 6 to Grade 7.

When looking at the specific construct of school climate, only three studies were found that applied LPA. Only one of these studies applied a standard application, while the two remaining studies included accommodations for nested data outside the use of a multilevel LPA (MLPA), rendering them non-standard applications.

Work by DiStefano et al. (2016) is an example of a standard LPA and is perhaps the most pertinent to the current study. DiStefano et al. (2016) applied a standard LPA using school climate data from 610 elementary schools (students and teachers) in South Carolina. The authors also used a three-step approach. This approach is designed to aid in the incorporation of covariates and distal outcomes without allowing them to improperly influence the composition of latent profiles that, in turn, misrepresent the data (Asparouhov & Muthén, 2014a; Lythgoe et al., 2019; Vermunt, 2010a). The general three

steps are to (1) estimate an unconditional model, (2) assign individuals to latent profiles, and (3) estimate the model again, with measurement parameters fixed at values that account for measurement error in profile assignment (Nylund et al., 2014). Covariates and distal outcomes can then be included in the model once the third step is completed (Nylund et al., 2014). More information on the three-step approach is provided in Chapter 3.

Distefano et al. (2016) included both covariates (school size and school poverty) and distal outcomes (school accountability performance measures). Profile solutions were determined based on the LMR-LRT p-value, as well as log-likelihood, AIC, BIC, and entropy values. While this study is similar in that it analyzed SC school climate data while including covariates and distal outcomes, it differs from the current study in that it did not account for the nesting of data and that it only created profiles for students at the elementary school level. The current study aims to fill in these gaps by assessing whether latent profiles exist for students and schools across all levels.

Looking beyond school climate in SC, Bradshaw et al. (2015) applied a non-standard LPA within the context of a longitudinal group randomized controlled effectiveness trial to examine population heterogeneity in universal School-Wide Positive Behavioral Interventions and Supports (SWPBIS: Sugai & Horner, 2006) program responsiveness. The SWPBIS is designed to foster a positive school climate and help schools address behavior problems (Bradshaw, Waasdorp, & Leaf, 2015). Student profiles were constructed based on teachers' baseline ratings of issues (e.g., behavior, concentration, socio-emotional functioning) among students in public elementary schools that adopted the universal SWPIS model. The clustering of individuals within schools

was accounted for by using the Huber-White adjustment (i.e., Huber Sandwich Estimator, sandwich algorithm; Muthén & Muthén, 1998-2017a). This estimator can be used to estimate the variance of the maximum likelihood estimate when an underlying model is incorrect, yielding standard errors that are robust to specification error (Freedman, 2006). Under strict normality conditions, variances for the maximum likelihood estimates are asymptotically correct, even when the specification, and thus likelihood function are incorrect (Freedman, 2006). However, the Huber-white adjustment does not account for the bias that occurs as a result of any specification error (Freedman, 2006).

The authors also found that profile membership moderated students' later need for school-based services and discipline problems, signaling that at-risk and high-risk children may benefit most from SWPBIS exposure. Relationships among profiles and a selection of covariates (i.e., grade, race, gender, free or reduced-price meal status, and special education status) were also evaluated. Significant relationships were located for both race and grade level covariates which were subsequently included in the final model. Indices used to evaluate alternative models included the log-likelihood, BIC, sample-size adjusted BIC, AIC, LMR-aLRT p-value, entropy score (see Ramaswamy et al., 1993), and the overall/relative size of the smallest class within each model.

The second non-standard LPA focused on school climate was conducted by Shukla and Konold (2018) with the goal to evaluate the validity of self-administered school climate questionnaires through the identification of atypical response patterns. Adopting a two-step process, response-inconsistency (RI) variables were created for each model factor to gauge the degree of response (in)consistency, with extreme values on either end highlighting potential response invalidity. Next, respondents with extreme

profiles across the RI variables (i.e., invalid latent class) were labeled as potentially invalid.

This procedure was conducted using data from the Virginia Secondary School Climate Survey which surveys students in grades 9-12. A total of 323 schools and 52,012 students completed the survey. The survey contained 100 Likert scale items (4-point) on student perceptions of school climate and safety, student activities, values, disciplinary infractions, and demographics. Factor loadings were computed based on a multilevel seven-factor confirmatory factor model. LPA groupings were based on patterns of RI values across the seven factors.

Descriptive data for LPA models included the means and standard deviations of RI variables for each factor. To evaluate alternative models, the AIC, BIC, LMR-aLRT, BLRT, and entropy values were considered. While the researchers assert that they performed a multilevel LPA, no evidence was provided to show that a multilevel LPA structure was used as the final model. There was no mention of a three-step method, but the authors did cite that the inclusion of auxiliary variables (e.g., academic outcomes, risk behaviors) took place after the initial parameter estimation of latent profiles. The authors did state that standard errors were calculated using the Huber-White estimator to account for nested data (Muthén & Muthén, 1998-2017a).

While the three aforementioned studies focus on the construct of school climate, much room exists for further study of LPA and advancement on the topic of school climate in the United States and in South Carolina. The current study is different from aforementioned research in several ways. First, it adopts a clear multilevel approach to LPA, looking at both student and school levels. Second, it accounts for students across

school levels (elementary, middle, and high). Third, it includes a unique set of covariates and distal outcomes at the student and school levels that have yet to be combined as it relates to student and school performance on school climate (e.g., college-and-career readiness). The elements that contribute to these differences will be described in further detail in the following sections. The next section describes the procedures that fall under multilevel latent variable modeling in more detail. It also includes a synopsis of the literature as it relates to school climate and the specific procedures intended for the current study.

Multilevel Latent Profile Modeling

Educational data is typically nested by nature. While the unit of analysis may be students, those students are often nested in classes, schools, districts, and so forth. A defining characteristic of LPA is its assumption of independence among observations. Not only does discounting the presence of nesting within data violate this assumption, but it can also result in inaccurate class enumeration and biased standard errors (Asparouhov & Muthén, 2008; Chen et al., 2010; Luo & Kwok, 2009; Makikangas et al., 2018; Meyers & Beretvas, 2006; Moerbeek, 2004; Park & Yu, 2016; Vermunt, 2003).

Multilevel models are designed to address these issues. Vermunt (2003, 2004) developed the multilevel latent class model (MLCM) which facilitates the modification of the independence assumption in the standard LCM. While the standard LCM operates under the assumption that model parameters are uniform across all observations (level-1 units), MLCM allows these parameters to vary across groups (level-2 units) (Vermunt, 2003). In other words, mixture models exist at two levels of the model, facilitating the

formation of latent profiles for both individuals and groups (Lukociene & Vermunt, 2010).

Many extensions have been made for the general MLCM over the years. Both fixed and random-effects models can be applied, with the latter having specifications for both parametric and non-parametric models where group-level latent variables are specified to have continuous or discrete distributions, respectively (Vermunt, 2003, 2004). Some researchers have presented the two-level MLCM as a three-level model in which indicator responses are nested within individuals which are then nested within groups, though the overarching methodologies appear to be synonymous (Lukociene & Vermunt, 2010; Skrondal & Rabe-Hesketh, 2004; Vermunt, 2008a). Others have added ‘common factors’ to MLCMs wherein the proportions of latent class memberships within latent clusters (level-2 latent profiles/classes) are viewed as indicators of a single, unobserved variable that represents the combined latent class structure within each cluster (Allison et al., 2016; Finch & French, 2014). Because the proportions of the within-cluster latent classes are assumed to be highly correlated with each other they are considered to be well-represented by a common factor (Finch & French, 2014; Henry & Muthén, 2010).

The remainder of this section details the general MLCM model and relevant extensions for the current study. Model selection criteria and implementation recommendations are also included, as well as discussion of recent applications in the literature.

General MLCM. The basic components of the MLCM include the observed responses for a given response indicator (i), individual (j), and group (k), or y_{kji}. The

number of response indicators is represented by $I(i = 1, \dots, I)$, and the number of individuals within group k and the number of groups are represented by $n_k(j = 1, \dots, n_k)$ and $K(k = 1, \dots, K)$, respectively. The total number of lower-level units is represented by the symbol N which is equivalent to $\sum_{k=1}^{K} n_k$. The vector of I responses of individual j from group k is $y_{kj} = (y_{kj1}, \dots, y_{kji}, \dots, y_{kjI})$, and the vector containing the full set of responses for group k is $\boldsymbol{y}_k = (\boldsymbol{y}_{k1}, \dots, \boldsymbol{y}_{kj}, \dots, \boldsymbol{y}_{kn_k})$ (Lukociene et al., 2010).

In an MLCM, individuals and groups are assigned to specific lower (i.e., level 1) and upper profiles (i.e., level 2), respectively. In the context of school climate, profiles at the lower and upper levels could be created for students and schools, respectively. Variables representing membership within the lower-level profiles are represented by x_{kj}, whereas those representing higher-level profiles are denoted by w_k. Further, the indicators within the specific profiles are denoted by $l(l = 1, \dots, L)$ for lower-levels and $h(h = 1, \dots, H)$ for the higher-levels (Lukociene et al., 2010).

Together, these components can be combined to form the two basic equations of the MLCM proposed by Vermunt (2003, 2008a). The first equation identifies the mixture model for the marginal density of the full response vector of a given group (Equation 6). In this equation, $P(w_k = h)$ is the probability that the group k belongs to a given latent class (h), and $f(\boldsymbol{y}_{kj} | w_k = h)$ is the conditional density for the response vector of individual j in group k, conditional on the membership of group k to latent class h.

$$f(\boldsymbol{y}_k) = \sum_{h=1}^{H} P(w_k = h) \prod_{j=1}^{n_k} f(\boldsymbol{y}_{kj} | w_k = h) \tag{6}$$

The second equation defines the mixture model for the last-mentioned component, the conditional density at the individual level (see Equation 7). The right side

of Equation 7 consists of two main components. The first is the probability that an individual within a given group belongs to a specific latent profile, given the group's latent class assignment, or $P\left(x_{kj}=l \middle| w_k=h\right)$. The second portion is $f\left(y_{kji} \middle| x_{kj}=l, w_k=h\right)$ and is the conditional density for a particular response indicator of an individual (in a given lower-level profile) who also belongs to a specific group (within a given higher-level profile) (Lukociene et al., 2010).

$$f\left(\boldsymbol{y}_{kj} \middle| w_k=h\right)=\sum_{l=1}^{L} P\left(x_{kj}=l \middle| w_k=h\right) \prod_{i=1}^{I} f\left(y_{kji} \middle| x_{kj}=l, w_k=h\right) \qquad (7)$$

The conditional densities are typically specified to belong to a given distribution, such as multinomial for categorical responses or normal distributions for continuous data. Because the current paper is focused on LPA which uses continuous indicator variables, the conditional density specification would be $f\left(y_{kji} \middle| x_{kj}=l, w_k=h\right) \sim N(\mu_{hl}, \sigma_{hl}^2)$, with class-specific means and variances.

Restricted MLCM. In the most general version of the MLCM, both the lower-level mixture proportions and the parameters defining the response densities are allowed to vary across higher-level profiles (Henry & Muthén, 2010; Lukociene et al., 2010). However, there are two special cases of the general model that place restrictions on the general model—parametric and nonparametric approaches. Both are considered random-effects approaches, meaning that rather than estimating a separate set of parameters for each group, group-specific effects are assumed to come from a certain distribution (Vermunt, 2003).

The parametric random effects approach makes strong assumptions regarding the mixing distribution, holding that level-1 intercepts are normally distributed around their

level-2 means (Bonito, 2019; Vermunt, 2003). More specifically, indicator variables are used to determine latent classes at level 1 which yield a random mean, or the proportion of individuals belonging to a given latent class (Finch & French, 2014). This mean can vary between clusters and is accompanied by random error. This error represents the level of uncertainty in the class assignments and can also vary between clusters (level-2 profiles) (Finch & French, 2014). Thus, in a parametric MLCM, data is represented by a standard latent profile model within clusters, and each cluster can be composed of varying proportions of different profiles; while the profiles themselves are composed of different proportions of individuals (Finch & French, 2014). While measurement equivalence is assumed across higher-level units (groups), groups are allowed to differ in the lower-level class membership of their members (Vermunt, 2010b).

In the nonparametric random effects approach, a discrete unspecified mixing distribution is adopted in lieu of the normal distribution used by the parametric approach (Vermunt, 2003). By using a multinomial distribution assumption, the approach avoids the strong distributional assumptions of the parametric approach, making it less computationally burdensome (Vermunt, 2003; Vermunt & van Dijk, 2001). In the eyes of some researchers, the use of an unspecified distribution makes the nonparametric approach more practical in that groups are classified into a smaller number of types rather than placed on a continuous scale (Vermunt, 2003).

With a nonparametric MLCM, individuals and groups are concurrently clustered, and the upper-level model structure is defined by upper-level latent profiles rather than the within-cluster proportions of responses at the lower level (Finch & French, 2014). Generally, individuals are assumed to belong to lower-level latent profiles that vary in the

distribution of the observed responses, while groups belong to higher-level latent profiles with contrasting distributions of latent profiles at the lower-level (Lukociene et al., 2010). More specifically, individuals are placed into within-cluster (level-1) latent profiles based on their responses to indicator variables. The proportion of within-cluster (level-1) profiles become indicators used in the assignment of these within-clusters to a between-cluster (level-2) latent profile (Finch & French, 2014). Thus, individuals within clusters are assigned to level-1 latent profiles and each cluster is assigned to a level-2 latent profile (Finch & French, 2014).

Studies have shown the parametric MLCM to computationally taxing and too restrictive compared to the nonparametric MLCM. These findings have held for two-level (Vermunt, 2003; Vermunt & van Dijk, 2001) and three/multi-level MLCMs (Vermunt, 2004) with latent classes. Vermunt (2008a) extended the application of discrete (nonparametric) MLCM to continuous response variables (i.e., latent profile analysis). While a statistical comparison of parametric and nonparametric MLCM was not performed, Vermunt did note that the use of a discrete approach proved to be extremely valuable as it facilitated the discovery of 'interesting and easy to explain patterns…that would never have been detected using a model with continuous latent [group] variables" (2008a, p.45).

In a more recent study, Finch and French (2014) analyzed parameter estimation accuracy and classification quality at the lower level of an MLCM using a Monte Carlo simulation. They found the parametric and nonparametric MLCMs to perform comparably well and recommended the nonparametric approach as useful default for

researchers given the occasional estimation problems displayed by the parametric approach in their study.

On balance, these findings support the use of a nonparametric MLCM in the current study. Given the size of the climate survey and number of respondents and groups, the nonparametric approach should be less computationally intensive. The ideas underpinning the use of nonparametric MLCM also align with a central goal of the study which is to identify both student and school profiles.

Nonparametric MLCM Specifics. The current section delves into specifics of the nonparametric MLCM approach. On a formulaic level, using this approach requires that the conditional density for a given response, or $P\left(x_{kj} = l, w_k = h\right)$, be constrained to equal $f\left(y_{kji} \middle| x_{kj} = l\right)$ leaving the latent profile assignment, $P\left(x_{kj} = l \middle| w_k = h\right)$, to be freely estimated (Lukociene et al., 2010). This constraint on the conditional response density implies that it is only affected by latent class memberships at the lower-level but not latent cluster memberships at the upper level. The result of this constraint is a simplified model with fewer parameters that yields more interpretable results compared to a parametric model.

Two main assumptions hold in the nonparametric MLCM (as well as general MLCM). First, observations of the individuals within a given group are assumed to be independent of one another, given the class membership of the group. The second is the local independence assumption which posits that the total number of response variables of an individual are assumed to be independent of each other, given their latent class memberships at both the individual and group levels (Bartholomew & Knott, 1999; Lukociene et al., 2010; McCutcheon, 2002b).

While assumptions for the MLCM may be similar to those of LPA, some implementation procedures are not. For example, the EM algorithm (Dempster et al., 1977) was modified by Vermunt (2003, 2007) to work effectively within a multilevel latent variable model. While maximum likelihood estimation is used to estimate an MLCM model, a specific implementation of the E-step is required when using the EM algorithm.

The standard implementation of the E-step involves the computation of the joint conditional expectation of the latent class variables as well as latent variables representing random effects—yielding an excessive number of latent variables, especially when there are more than a few level-1 units per level-2 unit (Vermunt, 2003). To correct this issue, the modified E-step capitalizes on the fact that the only components needed in this stage of the algorithm are the marginal posterior probabilities (i.e., posterior probability not conditioned on the values of other parameters) which can be directly computed (Vermunt, 2003). Latent variables are integrated or summed out by going from the lower-level to higher-level units, while the marginal posteriors are subsequently obtained beginning and ending with the higher- and lower-level units, respectively (Vermunt, 2003). The result is a more efficient calculation of marginal posterior probabilities vis-a-vis the implied conditional independence assumption within MLCM (Vermunt, 2003, 2004, 2005, 2008a). A more detailed explanation of the modified EM algorithm can be found in Vermunt (2008a).

A final consideration in the implementation of nonparametric MLCM involves the inclusion of auxiliary variables (i.e., covariates, distal outcomes). This is explained further in Chapter 3. However, it is important to note that it is possible to include

auxiliary variables at both levels of the nonparametric MLCM. For example, covariate effects can be tested at both levels by using multinomial logistic regression (Henry & Muthén, 2010). While latent profiles at the lower level can be predicted by covariates at either level, upper-level latent profiles can only be predicted by upper-level covariates which predict the probability that a group will belong to an upper-level latent profile (Henry & Muthén, 2010).

Model Quality. Apart from implementation considerations, model quality should also be carefully examined. The level of class separation as well as sample size are considered to be two of the most important factors that can influence the quality of a MLCM (Andrews & Currim, 2003; Dias, 2004; Lukociene et al., 2010; Sarstedt, 2008);

Entropy. A measure called entropy-based-R^2 (or R^2_{entr}) is often used to measure profile separation, or the degree to which profile memberships are predicted by the observed responses at both the higher- and lower-levels (Lukociene et al., 2010; Wedel & Kamakura, 1998). Values of zero indicate no profile separation, while values of one indicate perfect profile separation. At the lower level, R^2_{entr} depends on the number of lower-level profiles, the number of response variables, and the parameters defining the profile-specific response densities. Values at this level are best with a small number of profiles, many response variables, and larger differences in the profile-specific means with smaller within-profile variances when responses are continuous (Lukociene et al., 2010).

Entropy at the higher-level depends on the number of higher-level profiles, the number of individuals per profile, the number of profiles at the lower level, and the conditional probabilities across the higher-level profiles (Lukociene et al., 2010). Further,

the number of lower-level profiles affect entropy at both the lower and upper levels (Lukociene et al., 2010).

Sample Size. Looking to sample size, clear guidelines have yet to be provided as it relates to mixture models (Meyer & Morin, 2016). Park (2017) recommended that at least 20 groups are needed to have an accurate model, with low parameter and standard error bias and adequate coverage rates. Park (2017) also advises that each group should have 10-30 members to obtain reliable results, though this varies with model complexity the number of items. For overall sample size, Stanley et al. (2017) advise that small samples may result in inaccurate classifications and suggest a minimum sample size of 200 observations. Small sample sizes (< 300) may also require adjustments depending on model complexity (Meyer & Morin, 2016). However, researchers should still proceed with caution when employing large (n=500) or very large (n >1000) samples, as they can prompt statistically significant model-model comparisons or profile identifications that have no practical importance (Meyer & Morin, 2016).

Evaluating Model Fit. After evaluating the quality of each model, alternative MLCMs are compared to select the most appropriate model using a variety of tests and information criteria (similar to standard LCM). Two of the more popular tests for evaluating MLCMs are the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-aLRT; Lo et al., 2001; Vuong, 1989), and the parametric bootstrap LRT (BLRT; McLachlan & Peel, 2000) which are used in lieu of the likelihood ratio test (LRT) which is not recommended in LCM or MLCM (Nylund et al., 2007). Both can be used in single and multilevel latent profile models, and the most appropriate model is one that exhibits the most parsimony and has superior fit to a model with K+1 profiles (Masyn, 2013).

The LMR-aLRT approximates the LRT distribution with the aim of comparing the improvement in fit across neighboring latent class models (Nylund et al., 2007). It evaluates the improvement in fit from the $K - 1$ class model to the K class model and provides a p-value that can be used to determine whether an additional class significantly improves a given model (Nylund et al., 2007). Several studies have noted high performance of LMR-aLRT using Growth Mixture Modeling (GMM; Tofighi & Enders, 2007) and in LPA with well-separated classes (Lubke & Muthèn, 2007).

The BLRT also compares the improvement in model fit among K and K-1 class models. However, it does so by using bootstrap samples to estimate a log likelihood difference test statistic, thus empirically estimating the difference distribution rather than assuming it follows a known distribution (e.g., chi-square) (McLachlan & Peel, 2000; Nylund et al., 2007). In a study of single-level mixture models by Nylund et al. (2007), BLRT was found to outperform the LMR-aLRT test in terms of estimated Type I error and power while BIC outperformed the other studied ICs (AIC, CAIC, aBIC), especially for continuous indicator variables. The BLRT was also found to outperform the BIC, but its substantial computational time can impede its usage among researchers. As a result, the authors recommend that BIC and LMR-aLRT p-values be used to approximate BLRT values and that other measures be used if standard difference testing is needed (Nylund et al., 2007). While this measure has been touted to be one of the most accurate and consistent likelihood ratio tests for class enumeration, it has yet to be systematically studied in relation to multilevel models (Park, 2017).

Information criteria (IC) such as BIC, aBIC, AIC, and CAIC can be used in addition to the aforementioned tests when selecting the most appropriate model.

Lukociene et al. (2010) compared the performance of ICs among parametric and nonparametric specifications and continuous/categorical indicators of multilevel latent variable models.

With continuous indicators (MLPA), the BIC(K) was found to be the preferred method, where K is the number of groups. This was determined to be the only appropriate sample size for deciding about the number of higher-level classes and is in agreement with results reported by Lukociene and Vermunt (2010). When the decision concerns lower-level profiles/classes, it makes less of a difference wither K or N (number of lower-level units/observations) is used, but K still outperforms N (Lukociene et al., 2010). The consideration of level-1 and level-2 groups is not needed for the single-level LPA. Thus, the standard BIC is recommended when analyzing single-level mixture models with continuous data, though at times it can underestimate the number of latent profiles if sample size is small or class enumeration is low (Fonseca & Cardoso, 2007; Hagenaars & McCutcheon, 2002; Magidson & Vermunt, 2004; Park, 2017; Yang, 1998).

The relative performance of information criteria varies depending on a variety of factors. Looking at multilevel latent class analysis using categorical observations, Lukociene and Vermunt (2010) found that BIC(K) and CAIC(K) performed very well when the level of separation and sample size were large enough. But overall, they concluded that AIC3 (Bozdogan, 1994) was the best fit measure. The AIC3 uses the value of 3 as the penalty for adding an additional parameter instead of the 2 used in a standard AIC (Park, 2017). While the AIC3 has demonstrated high performance in simulations and has been recommended by several researchers (Andrews & Currim, 2003; Fonesca & Cardoso, 2007; Yang & Yang, 2007), others argue that lacks a

theoretical basis. Further, as mentioned previously, it seems to underperform the BIC when continuous observations are analyzed within a model (Dziak et al., 2012).

The findings above illustrate that the performance of various indicators is context specific. Further, while a variety of likelihood measures and fit indices exist, there is currently no consensus in the statistical literature on the best class enumeration methods for multilevel or single-level latent profile analysis (Cubaynes et al., 2012; Chen & Jiao, 2014; Nylund et al., 2007). For this reason, identification of subgroups within a mixture model should be determined using multiple measures and with special attention to data characteristics such as profile separation, profile size, and sample size. The following section includes various studies on multilevel mixture modeling that further illustrate this point.

MLPA and School Climate. As with LPA, school climate applications of MLPA are largely absent in the literature. A search of peer-reviewed articles suggests that the majority of educational studies apply MLCA rather than MLPA procedures. The same pattern applies to nonparametric/parametric MLCA and MLPA applications. To provide a richer background on the applications of multilevel mixture modeling in the contexts of education and school climate, MLCA and MLPA applications are discussed, with and without parametric or non-parametric specifications.

General education-related studies using multilevel latent variable analyses (MLCA and MLPA) differ in focus, varying from teaching strategies to student psychological well-being (Jung et al., 2019; Warwas & Helm, 2018). Among MLCA studies is a dissertation paper by Graves (2019) that evaluated educational leadership, information technology (IT), and culturally responsive education using nonparametric

MLCA to identify teacher typologies and perceptions. Gohari et al. (2020) also applied a nonparametric MLCA to identify patterns of alcohol use among Canadian students. Several studies applied nonparametric or standard MLCA to identify latent classes using data from large-scale student assessments such as the Programme for International Student Assessment (PISA) and the Dutch national mathematics assessment (Fagginger et al., 2016; Finch & Marchant, 2013; Van De Vijver et al., 2019; Yalcin, 2017). Another MLCA was conducted in an educational setting was one by Tomczyk et al. (2017) where substance abuse patterns were evaluated within a longitudinal sample of 2,490 German students in 45 schools and four German states. They included sociodemographic covariates including age, gender, and socioeconomic status.

Looking to general education-related studies applying MLPA, the field was considerably narrowed. Dietrich et al. (2019) applied a parametric MLPA to look at undergraduate students and motivation. Gray (2017) also used MLPA to evaluate perceptions of fitting in among 702 high school students in 33 classrooms while including covariates of race and free/reduced price lunch.

In a search for MLCA and MLPA studies directly related to school climate, a few studies emerged. Again, applications of MLCA outweighed those for MLPA. Mayworm (2016) performed an LCA, as well as a parametric and nonparametric MLCA with the 3-step approach. School discipline climate was analyzed using responses from the 2002 Education Longitudinal Survey (ELS) by the National Center for Education Statistics (NCES). Data was collected across 12,610 students nested in 580 public high schools.

The nonparametric MLCA with four classes at level 1 and three classes at level 2 was chosen as the final model. Level 1 classes were labeled as: uninvolved, authoritarian,

permissive, and authoritative. The authoritative class perceived high teacher support, rule fairness and school disciplinary structure. Students in the permissive class denoted a high perception of teacher support and a moderate-to-low disciplinary structure. The authoritarian class perceived a moderate-to-low teacher support and rule fairness, but high school disciplinary structure. And the uninvolved student class represented students who perceived both low teacher support and low school disciplinary structure. Level 2 classes were labeled as: mostly authoritative, mostly permissive, and mostly authoritarian. These classes were composed of different percentages of the student-level classes.

Low levels of entropy precluded the inclusion of distal outcomes. However, covariates at both the levels were also included. Gender, race/ethnicity, and SES served as student-level covariates. School-level covariates included enrollment size, percentage of students receiving free and reduced-price lunch, and racial composition. The covariates of student gender, ethnicity/race, and SES were all found to impact students' class membership. Surprisingly, none of the school-level covariates had an effect on school-level latent class membership, though school size was excluded from the final analysis. Because all covariates were simultaneously included in the model, the author suggests that student-level covariates may have negated school-level covariate effects and calls for further research on school-level demographic indicators.

In an application of nonparametric MLCA, Allison et al. (2016) attempted to locate classes of high school students based on their responses to 10 health-related indicators, some of which can be extended to issues of school bullying and climate. A total of 3,000 students within 103 geographically dispersed high schools were analyzed.

Covariates were included at both the student and school levels using multinomial logistic regression. Low household income (covariate) corresponded to higher odds of attending a distressed school, suggesting that SES may be related to school settings associated with distressed (and bullied) students, consistent with existing research (Due et al., 2009; Goodman et al., 2003; Jablonska et al., 2014; Saab & Klinger, 2010).

One study that applied MLPA in the context of school climate was performed by Van Eck, et al. (2017). A nonparametric MLPA with covariates at both levels was performed to investigate the relationship between school climate and chronic absence among students in grades 6-12 across 106 at-risk urban schools. The nonparametric specification meant that school-level profiles were the individual level profiles rather than the individual-level indicators (Van Eck et al., 2017). The multilevel modeling framework outlined in Asparouhov and Muthén (2008) and Henry and Muthén (2010) was used to analyze students' perceptions of school climate as well as the overall impact of school climate perceptions at the school level (Van Eck et al., 2017). It appears as though the authors employed a three-step method, though it was not directly specified.

The authors argue that they were among a select few to use latent person-centered modeling strategies to identify school climate profiles. Their model was evaluated using BIC and AIC information criteria as well as BLRT and LRT in selecting the individual-level model. The primary covariate of interest in the study was school-level chronic absence, with other school-level covariates relating to school demographics (i.e., student-teacher ratio, middle vs. high school) and school-level student characteristics (i.e., percent male, free meals, student mobility). The sole individual-level covariate was gender. While the study by Van Eck et al. (2017) is one of a few to apply nonparametric

MLPA to school climate, it did have some limitations. Only one school district was analyzed, and this district was fairly homogenous with the sample consisting mostly of African American students from urban areas. Also, as is the case with most survey responses, the data were not missing at random.

As one can see from the current literature concerning school climate and multilevel mixture modeling, several studies have conducted an MLCA or MLPA using a three-step approach with the inclusion of covariates. However, none have effectively used a nonparametric MLPA while including distal outcomes and covariates using a manual, bias-adjusted BCH three-step approach. .

The Three-Step Approach.

On balance, the three-step approach aids in the incorporation of auxiliary variables within a model. While some mixture modeling applications center only on the discovery of latent profiles, some researchers decide to take it a step further by examining the relationship between individual membership within these profiles and other observed variables, commonly referred to as auxiliary variables. There are two types of auxiliary variables: covariates and distal outcomes. Covariates are seen as predictors of the latent variable, while distal outcomes are seen as consequences of latent class membership (Asparouhov & Muthén, 2014a; Nylund-Gibson et al., 2019). Because covariates and distal outcomes are seen as predictors or products of latent class membership, they are not included as part of the measurement model that reflect and define latent classes based on a set of individual responses (Nylund-Gibson et al., 2019; Vermunt, 2010a).

Auxiliary variables enhance the flexibility of mixture models. However, their inclusion also highlights the current debate concerning proper class enumeration in the

field. More specifically, in incorporating covariates and distal outcomes into latent class/mixture models, some researchers treat them as indicators within the measurement model (Shin, No, & Hong, 2019; Nylund et al., 2007). This can influence the composition of the latent profiles and result in profiles that misrepresent the data (Asparouhov & Muthén, 2014a; Lythgoe et al., 2019; Vermunt, 2010a).

The aforementioned issue is most prevalent in the application of the 'one-step approach' (Bandeen-Roche, et al., 1997) which assumes that the classification model is built in the same stage as the model used to predict class membership (Asparouhov & Muthén, 2014a). To address this issue, researchers have developed a vast array of methods including the pseudo-class method, the classify-analyze approach (Clogg, 1995), the two-step approach (Bakk & Kuha, 2018), pseudo-class draw approach (Asparouhov and Muthén, 2007; Petras & Masyn, 2010; Wang, et al., 2005), and a number of three-step approaches including the ML (Vermunt, 2010a), BCH (Bakk et al., 2014; Bolck et al., 2004; Vermunt, 2010a), and LTB methods (Lanza et al., 2013).

Both the two- and three-step approaches have recently received much attention in the literature due to a vast array of problems found within the other methods (see Bakk et al., 2013; Gudicha & Vermunt, 2013; Nylund-Gibson et al., 2019; Petersen et al., 2012; Vermunt, 2010a). While the two-step approach shows promise, it is currently not recommended for use among applied researchers as it is not widely supported by statistical software (Nylund-Gibson et al., 2019; Shin et al., 2019). Thus, three-step approaches have become popular way to address the inclusion of auxiliary variables in mixture modeling procedures.

As previously mentioned, there are several three-step approaches from which to choose (e.g., BCH, ML, LTB). Comparisons of these approaches and subsequent recommendations frequent the literature. Looking at the inclusion of covariates, Gudicha and Vermunt (2013), found that BCH and ML methods both performed well except when class separation was very low and sample size was small. They found that while the BCH approach had lower bias than the ML approach, it was also relatively unstable and less efficient. Asparouhov and Muthén (2014b) acknowledge that it is possible for standard errors (SEs) to be underestimated with the BCH approach when entropy is low but recommend it as the preferred method for continuous distal outcomes if one is concerned about class formation changes between steps. They also highlight the ML approach as a preferred method when there are no class formation changes. When categorical distal outcomes are used, they recommend the LTB approach by Lanza et al. (2013). And with the presence of covariates, Asparouhov and Muthén (2014b) suggest that the 'R3STEP', or manual BCH approach, be used.

Bennink et al. (2015) conclude that either BCH or ML could be used as long as class separation is sufficient ($R^2_{entr} = .45$) and independent of whether modal or proportional assignment is adopted. However, work by Bakk et al. (2016) found the LTB approach to be more efficient than the BCH approach, though both were observed to perform comparably with regard to parameter bias and this approach is not recommended by Nylund-Gibson et al. (2019).

In a simulation study by Bakk and Vermunt (2016), violations of normality and equal variance across classes for continuous distal outcomes were examined in terms of bias and coverage rates (i.e., the number of replications with confidence intervals that

contain the true population parameter) (Nylund et al., 2007). Results illustrated that the BCH approach was more robust when distal outcomes are included and that the ML approach was preferred when covariates are included in the model (Bakk & Vermunt, 2016). Other studies examining the impact of non-normality of distal outcome distributions also recommend the BCH method (Asparouhov & Muthén, 2014b; Dziak et al., 2016; Shin et al., 2019).

Interestingly, the majority of studies surrounding three-step approaches focus on LCA rather than LPA. Dziak et al. (2016) were among the few to break this trend with the comparison of 3-step approaches using LPA and a variety of conditions, including various distal outcome distributions (i.e., binary, homoscedastic normal, heteroskedastic normal, and skewed). For binary outcomes, both ML and BCH approaches performed similarly with regard to bias and coverage rates, but BCH outperformed ML with regard to estimation error. With continuous outcomes, BCH generally outperformed ML regarding bias, estimation error, and coverage. Thus, the researchers suggested that the BCH may be the best approach for including distal outcomes in LPA, reflecting similar findings by Bakk and Vermunt (2016) for LCA.

Collier and Leite (2017) also compared BCH, LTB, and pseudo-class draw (PC; see Asparouhov & Muthén, 2007; Petras & Masyn, 2010; Wang et al., 2005) approaches across latent class and latent profile models. They examined models with both covariates (BCH, PC) and distal outcomes (BCH, LTB, PC) based on the relative bias of coefficient estimates, the relative bias of standard error estimates, coverage rates, Type I error, and power (LTB can only be used with a single distal outcome). The performance of these methods varied by simulated levels of entropy, effect size and sample size. The

researchers found that for LPA, the BCH method yielded more accurate estimates compared to PC for both covariates and distal outcomes. However, when considering only distal outcomes, the LTB had the lowest relative bias of coefficient estimates and the best Type I error rates compared to the other methods.

Because these methods are continuously being adjusted and compared on a variety of indicators by a number of researchers, it is difficult to determine which method is best suited for a given set of research questions. Nylund-Gibson et al. (2019) conducted a thorough review of the current methods and recommended that either the BCH or ML approach be used when examining distal outcomes, given that they are manually entered by the researcher and the default program is not used.

Benefits of the manual BCH include its performance with all continuous distal outcomes, ability to include both covariates and distal outcomes, and robustness with unequal class-specific variances (Nylund-Gibson et al., 2019). Among its weakness is its inability to include more than one latent class variable. Further, BCH weights could become unstable (negative) with low entropy or small sample size, preventing the computation of class-specific distal outcome means (Nylund-Gibson et al., 2019). Though, this can be alleviated if variances are constrained to equality, assuming the researcher is not interested in class-specific variances.

Nylund-Gibson et al. (2019) found the manual ML approach be flexible—allowing the inclusion of more than one latent class variable as well as the simultaneous inclusion of covariates and distal outcomes. They also assert that manual ML approach is robust when class-specific variances of distal outcomes are unequal. Disadvantages of the approach include its increased complexity and the increased vulnerability to shifts in

latent-class membership from Step 1 to Step 3 compared to the BCH approach, as is explained in the next section (Nylund-Gibson et al., 2019).

Research on the various three-step approaches shows that both the ML and BCH methods are acceptable. However, the BCH method appears to be more valuable in the context of latent profile analysis and distal outcomes for the current study.

Role of the Current Study

The previous review of the procedures of LPA and MLPA and their applications within the context of school climate highlights the usefulness of using a person-centered, multilevel model when analyzing school climate data. As the majority of school climate studies focus on variable-centered approaches, the use of a person-centered approach should provide insight into an often neglected view of school climate. In the current study, students are also nested within schools. Conducting a MLPA will account for this nesting and assist in the proper assignment of individuals to latent profiles. To date, this has not been done using the SC school climate student data, and very few other studies have used a nonparametric MLPA to identify both student and school profiles of school climate. The current study will be the only one to apply a nonparametric MLPA using the BCH 3-step method with both covariates and distal outcomes on a state-wide sample of students in elementary, middle, and high school.

While DiStefano et al. (2016) conducted LPA on SC school climate student data from 2013, the current study expands on this by adding a multilevel model component, including a different distal outcome, and looking across all school levels. The hope is that the inclusion of a multilevel structure will both aid in the correct classification of individuals and provide further insight into school climate differences across schools by

allowing for the formation of school-level latent profiles which has yet to be studied on the SC school climate survey for students.

The addition of covariates and distal outcomes is also of importance. Poverty has been previously included as a covariate in class formation, but it has not been applied to a multilevel structure. The addition of a upper-level covariate will allow us to understand how different profiles of students and schools are impacted by poverty and how this relates to respective climate profiles. Further, the distal outcome(s) of the current study differ from those presented in the study by DiStefano et al. (2016). Specifically, the current study includes a school-level distal outcome for career-and-college readiness in addition to an academic achievement outcome measure.

On balance, the current study seeks to fill a gap in the literature. Little has been done to identify latent profiles of school climate when compared to the vast amount of literature that exists on the topic. Grouping students and schools by shared characteristics can help policymakers and school administrators to better understand and address the variety of challenges our students and schools face on a daily basis. It can also aid in the proper distribution of district and state services that can be better targeted to schools with varying combinations of student climate profiles. The mechanisms by which the current study will address the shortcomings in the literature and contribute to the knowledge of SC school climate are presented in Chapter 3.

CHAPTER 3

METHODS

While the underlying structure of SC school climate surveys have been previously studied, they have yet to be analyzed with more advanced methods. Specifically, SC school climate has not been analyzed using a nonparametric multilevel latent profile analysis (MLPA) with a bias-adjusted three-step approach to assist in the inclusion of covariates and distal outcomes. A central aim of the current study is to identify school climate profiles at the school and student levels and to evaluate the relationships between these profiles and poverty, career/college readiness, and academic achievement, as outlined in Research Question 1. An additional objective is to place the applied procedures, specifically the use of item-level data and the manual BCH 3-step, under an evaluative spotlight from both methodological and policy perspectives, as outlined in Research Questions 2 and 3.

This chapter is devoted to the discussion of the methods through which the aforementioned objectives can be met. The choice to apply a MLPA was guided by the desire to locate both student and school latent profiles while also accommodating the nested nature of the data. The three-step approach was used to incorporate important covariates and distal outcomes that will provide greater insight into the differences between profiles while also ensuring that their inclusion does not wrongly influence their construction. The decision to adopt a nonparametric specification of MLPA was based on the desire to avoid making strong distributional assumptions and to yield more practical groupings of schools based on the distribution of individual-level profiles. And, as will be discussed later in this chapter, a bias-adjusted three-step approach (in this case, the

manual BCH approach) was implemented because it appears to be more valuable than other approaches in the context of latent profile analysis and distal outcomes.

It should also be noted that the selection of the manual BCH approach for the current study was, in large part, based on its status as a relatively new approach with few applications to using school climate survey data. The novelty of this approach was further expanded by the planned incorporation of a multilevel model, of which little to no guidance was presented in the literature. From this perspective, the current study took on a somewhat exploratory and experimental approach by applying a relatively new method in a unique way to data that had not yet been analyzed within it.

Adopted methods for the preparation and analysis of data are thoroughly described in the subsequent sections of this chapter. The first section discusses the manner in which data was collected and is followed by a section on data cleaning and preparation. This is followed by a section on data analysis procedures that contains several subsections on model specifications and analytical approaches used to evaluate the model of interest. The final section provides a step-by-step outline of how the methods were applied in the current study.

Instrumentation and Data Collection

The state of South Carolina collects school climate data annually from teachers, students, and parents. In the current study, only data from students were used. Survey instruments are administered to students in the highest grade level at each school in the entire state (typically 5, 8, and 11), though students in Grade 12 are not targeted. The survey contains 52 Likert-scale items measured on a four-point Likert scale (with anchors of 1=Disagree, 2=Mostly Disagree, 3=Mostly Agree, and 4=Agree). Items address

learning environment (n=18 items), social-physical environment (n=18 items), home-school relations (n=8 items), and bullying (n=8 items). Students completed the surveys using an online platform.

The school climate dataset contained information from 1,219 public schools and 157,824 observations across South Carolina. The population of interest was considered to be all public-school students in South Carolina. Among all actively enrolled students during the 2017-2018 school year, 33.6% were black or African American, 50.6% were White, 9.7% were Hispanic or Latino, and over 6% identified as American Indian, Asian, Hawaiian, Pacific Islander, or biracial (South Carolina Department of Education, 2018). Female and male students composed 48.9% and 51.1% of the student population, respectively (South Carolina Department of Education, 2018). While the student school climate survey does not collect the aforementioned data in an effort to increase response rates and protect respondents' privacy, the information is provided to describe the population from which the sample was drawn.

Data Cleaning and Preparation

Prior to conducting analyses, data were cleaned and prepared for inclusion in both the latent profile and multilevel latent profile procedures. The 2018 dataset was imported into SAS (Version 9.4) with 157,824 observations and 52 item variables. Unfortunately, errors in data collection or entry have historically resulted in the presence of illegitimate duplicate responses. Identical response patterns and count mismatches between the expected number of students within a given school and the number of received responses were indicative of duplicate responses. Duplicates were removed using the NODUPRECS command which does not consider missing values in eliminating missing

values. This procedure removed 9,389 observations, leaving 148,435 observations. Reverse coding was performed on negatively-worded items.

Prior exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) procedures revealed the presence of four factors in the dataset: learning environment, social/physical environment, home school relationship, and safety. The final item-factor solution was consistent with previous research on SC school climate surveys (see Appendix C for list of survey items by survey section). Bullying items were excluded from this factor analysis as they are not currently used by the state department or SCEPC to create school climate profiles and were therefore removed from the dataset. Items that did not load well onto a factor during factor analysis and were categorized as 'other' were also excluded. One item (Q35: My school as a variety of extracurricular activities for students) was only present in surveys at the high-school level and was removed for purposes of the current analysis. Removal of these items resulted in a dataset with 34 item-related variables.

Next, observations with 25% or more of responses missing within the originally assigned survey section (Learning Environment, Social-Physical Environment, Home-School Relationships) were removed. This resulted in the deletion of 1,716 observations, leaving 146,719 records remaining. Mean imputation for observations with less than 25% missing responses within a section was then conducted. Missing values were replaced with the individual's average score for the other items within its respective section.

Looking within each school, 208 observations across 50 schools were removed because each school had less than 15 observations assigned to it. Observations attached to schools that were not specifically categorized as elementary, middle, or high (e.g., those

having multiple categorizations or identified as primary) were removed from the dataset. Finally, Likert scale responses for each observation were then standardized to have a standard normal distribution, $Z \sim N(0,1)$, by school level (elementary, middle, high). School-level auxiliary variables for school poverty, academic achievement, and college/career readiness were also joined to the dataset. The final dataset for use in LPA analysis had a total of 129,587 observations across 1,023 schools and 46 variables.

It should also be noted that data were treated as continuous. Although Likert data are used with the climate surveys, research shows that the presence of four or more item response categories yields similar results if data are symmetric, regardless of whether categorial or continuous estimation procedures are used (Finney & DiStefano, 2013). This finding supports the decision to treat data as continuous when identifying the item-factor structure used to evaluate profile-level results at later stages of the analysis.

Data Analysis

The data analytic procedures adopted in the current analysis of SC school climate data are explained in this section. These procedures are organized into three subsections. Model assumptions and restrictions are discussed in the first subsection. The second subsection pertains to the adopted model structure, specifically the multilevel and nonparametric specifications that were discussed in Chapter 2 The analysis approach with particular attention given to the BCH 3-Step procedure used is discussed in the third subsection. Because this approach was not discussed in Chapter 2, it is discussed at greater length than the model-related procedures in the first subsection.

Model Assumptions to Consider

As previously discussed, several assumptions are made when applying mixture models. The first pertains to local independence which posits that all indicator variables are uncorrelated within each profile and that all profile-specific off-diagonal covariance elements are zero (Spurk et al., 2020, p.3). The second assumption relates to homogeneity of variance wherein all profile-specific covariance matrix elements along the main diagonal are held equal across profiles (Lubke & Neale, 2006; Spurk et al., 2020; Vermunt & Magidson, 2002). Finally, the assumption of multivariate normality must be met, though this can be easily accommodated through use of the full-information ML estimator (MLR) that is robust to non-normality for ordinal Likert data with four or more categories (see Finney & DiStefano, 2013).

While mixture models are automatically constrained to hold these assumptions in the Mplus software (Version 8.6; Muthèn & Muthèn, 1998-2017b), researchers have the ability to relax them to meet the needs of their research. In fact, failure to recognize and modify the assumptions of local independence and homogeneity of variance can lead to model misspecification. More specifically, it can result in an over-estimation of the true number of profiles and a more inaccurate performance of fit indices (Peugh & Fan, 2013; Spurk et al., 2020).

However, not all models are created equal and research using very large datasets with many items or large sample sizes may face difficulty running and/or interpreting models with these assumptions relaxed. The options related to the relaxation of the aforementioned assumptions were weighed carefully and are discussed in greater detail in Chapter 4.

Model Specifications

A nonparametric specification of the MLPA was applied to the current study. As previously discussed, many studies of school climate also fail to account for the natural nesting of educational data (e.g., students within schools). Person-centered studies of school climate are also a rarity. The current study accounted for nesting and incorporated a person-centered perspective by applying MLPA.

Another model-based specification was the choice to use a nonparametric random effects model which uses a discrete unspecified mixing distribution instead of a normal distribution. By using a multinomial distribution assumption, this approach avoids the strong distributional assumptions of the parametric approach, making it less computationally burdensome (Vermunt, 2003; Vermunt & van Dijk, 2001). An unspecified distribution makes the nonparametric approach more practical in that groups are classified into a smaller number of types rather than placed on a continuous scale (Vermunt, 2003). Further, given the size of the climate survey and number of respondents, the nonparametric approach was considered to be less computationally intensive. Finally, the use of nonparametric MLPA also permitted the identification of both student and school profiles, which is an aim of the current study.

Approach to Analysis: The BCH Method

This study will utilize a specific application of the three-step approach Referred to as the BCH method. The BCH method of implementing the three-step approach consists of three general steps. First, the researcher identifies the best-fitting unconditional model using the profile/class-enumeration process without the auxiliary variable(s) (Nylund-

Gibson et al., 2019). This step will yield posterior probabilities of class/profile membership for each individual and each class/profile (Huang et al., 2017).

In the second step, individuals are assigned to latent classes/profiles based on their posterior class membership probabilities (W) which are calculated from the parameters in Step 1 using Bayes' rule (see Equation 8; Bakk & Vermunt, 2016).

$$P(X = t|\boldsymbol{Y}_i) = \frac{P(X=t)P(\boldsymbol{Y}_i|X = t)}{P(\boldsymbol{Y}_i)} \tag{8}$$

In the above equation, $P(X = t)$ is the unconditional probability of membership in class t and $P(Y_i|X = t)$ is the conditional class-specific distribution of the response vector Y_i. Assignment can be done using either modal or proportional assignment, though studies have shown both to work comparably well within the bias-adjusted BCH approach. Modal assignment assigns each individual to a single class (e.g., Class A=1, Class B=0), whereas proportional assignment assigns individual probabilities for each of the classes (e.g., Class A=.75, Class B=.25).

Classification errors often result from these assignment procedures and are compiled for each of the observed response patterns. They are then presented as the probability of an assigned class membership (s) conditional on the true class membership (t) as shown in Equation 9 (Bakk et al., 2013; Vermunt, 2010a; Bakk & Vermunt, 2016).

$$P(W = s|X = t) = \frac{\sum_{i=1}^{N} P(X = t|Y_i)P(W = s|Y_i)}{N\,P(X=t)} \tag{9}$$

Finally, in Step 3, the class assignments (W) are used to estimate the relationship between the latent variable (X) and the auxiliary variable (Z). The inverse logits of the individual-level classification errors computed in Step 2 are incorporated into this process, serving as a type of bias correction (Bakk et al., 2013; Nylund-Gibson et al.,

2019). As a result, the model displayed in Equation 10 is used where both Z and W serve as response variables and $P(W = s, Z_i)$ is fixed, or known (Bakk & Vermunt, 2016).

$$P(W = s, Z_i) = \sum_{t=1}^{T} P(X = t) f\ (Z_i | X = t) P(W = s | X = t) \tag{10}$$

The BCH approach estimates the above model using weighted analysis. An Analysis of Variance (ANOVA) model is estimated using only observed variables. The true latent classification is recreated by taking the inverse of the individual classification errors and using them as weights for the latent class assignments (Bakk & Vermunt, 2016; Bolck et al., 2004; Vermunt, 2010a;). A pseudo-maximum likelihood estimation procedure is used to estimate the resultant model, using robust standard errors to account for the multivariate nature of the data and the weighting procedure (Bakk et al., 2014; Bakk & Vermunt, 2016; Vermunt, 2010a).

Stages of the Chosen Analysis Procedure

The stages of analysis for applying a nonparametric MLPA using the manual BCH three-step approach and multilevel three-step methods are outlined in the following subsections. Analyses were conducted using SAS (Version 6) and Mplus (Version 8.6, Muthén & Muthén, 1998-2017b). Model-building and estimation processes were largely guided by the works of Nylund-Gibson et al. (2019), Asparouhov and Muthèn (2021), and Makikangas et al. (2018).

Robust maximum likelihood estimation was conducted using the MLR estimator which is robust to non-normality and non-independence of observations. The EM algorithm was used in lieu of the accelerated EM (EMA) procedure which is the default for mixture models in Mplus. The EMA supplements the steps of the EM with Quasi-Newton (QN) or Fisher-Scoring (FN) optimization steps when the EM shows a marked

decrease in speed and shows little change in the log likelihood value over several iterations (Muthén, 2004; Muthén & Muthén, 1998-2017a). Both unconditional models and the model in Step 1 of the manual BCH 3-Step procedure were re-evaluated with at least twice the number of random starting values as the initial estimation to ensure that the best log likelihood value was replicated. Random starting values were not used in Steps 2 and 3 of the manual 3-Step procedure as recommended by Asparouhov & Muthèn (2021).

Stage 1: Estimate Unconditional LPA and MLPA Models

Prior to using the manual BCH 3-Step procedure, the appropriate number of profiles must be identified for both the student and school levels. The following sections outline the steps used to carry out this process in the current study.

The Unconditional LPA Model. As discussed previously, the traditional single-level LPA procedure is used to help a researcher identify the most appropriate number of latent profiles of individuals using an iterative process. A selection of contending models are then compared using a variety of criteria. The most appropriate model is typically one that exhibits the best model fit indices and model parameters while remaining theoretically sound.

In the current study, LPA models with one to six profiles were evaluated using the fit indices presented in Table 3.1. The AIC, BIC, adjusted BIC (aBIC), LMR-LRT,LMR-aLRT were used to measure relative fit, while LL served as a measure of absolute fit. To evaluate classification precision across alternative models, AvePP and OCC were used. Entropy was employed as a measure of classification uncertainty.

In addition to the set of indices detailed in Table 3.1, class-specific item parameters are examined to evaluate model fit. Because an LPA has continuous outcomes, these take the form of item means and variances (Nylund et al., 2007). While variances are held constant in the current study, item means were evaluated. Profile counts and proportions and classification probabilities were also examined across profiles for each model. Finally, elbow plots of fit indices and bar graphs for each item within each profile were created to visually examine item differences across profiles and previously-identified factors to select the best-fitting model.

Table 3.1*Fit Indices and Measures*

Index	Type	Interpretation	Reference(s)
LL	Absolute fit	Higher values denote better fit, but are a function of sample size	Masyn (2013)
LMR-(a)LRT	Relative fit	K vs. k-1 class comparison. Significant p-value indicates improvement in model fit by adding a class.	Lo et al. (2001)
AIC	Relative fit	K vs. k+1 model comparison, selecting model showing the largest decrease in value.	Akaike (1974)
BIC	Relative fit	K vs. k+1 model comparison, selecting model showing the largest decrease in value.	Schwarz (1978); Raftery (1995)
aBIC	Relative fit	K vs. k+1 model comparison, selecting model showing the largest decrease in value.	Sclove (1987)
AvePP	Classification precision	Value > .70 indicates adequate separation and classification precision.	Masyn (2013), Nagin (2005), Wong (2019)

Index	Type	Interpretation	Reference(s)
OCC	Classification precision	Value >.5 for all classes, preferably closer to 1.	Nagin (2005), Van der Nest et al. (2020)
Entropy	Classification uncertainty	Bounded by 0 and 1. Large values indicate better class separation.	Ramaswamy et al. (1993)

The Unconditional Nonparametric MLPA Model. Once the final one-level model is identified using the traditional LPA, similar steps are carried out to identify the unconditional nonparametric MLPA model for use in the BCH 3-Step procedure. Figure 3.1 displays a nonparametric MLPA model akin to the one used in the present study. At Level 1, the U represents a model factor and the C represents the collection of Level 1 latent profiles with the black dots denoting $C - 1$ profiles estimates produced by the model at the lower level. The CB signifies the distribution of the Level 1 profiles across the set of Level 2 profiles, and $C\#$ is the mean of a given profile across Level 2 units.

Recall that the nonparametric MLPA approach assumes a multinomial distribution rather than the normal distribution adopted in the parametric approach (Vermunt, 2003; Vermunt & van Dijk, 2001). Also, recall that indicators at the school-level are the individual-level profiles, not the individual-level indicators (Van Eck et al., 2017). This creates upper-level profiles based on prevalence of each lower-level profile.

Nonparametric MLPA was conducted across models with two to four upper-level profiles with the number of lower-level profiles during the previous step held constant. The nonparametric MLPA model deemed to have the most appropriate fit was selected for use in the manual BCH 3-Step process. Similar to the LPA, model fit, and

interpretability were assessed using log likelihood, LMR-aLRT, AIC, BIC, aBIC, entropy, and the interpretation of item-profile counts, proportions, and patterns.

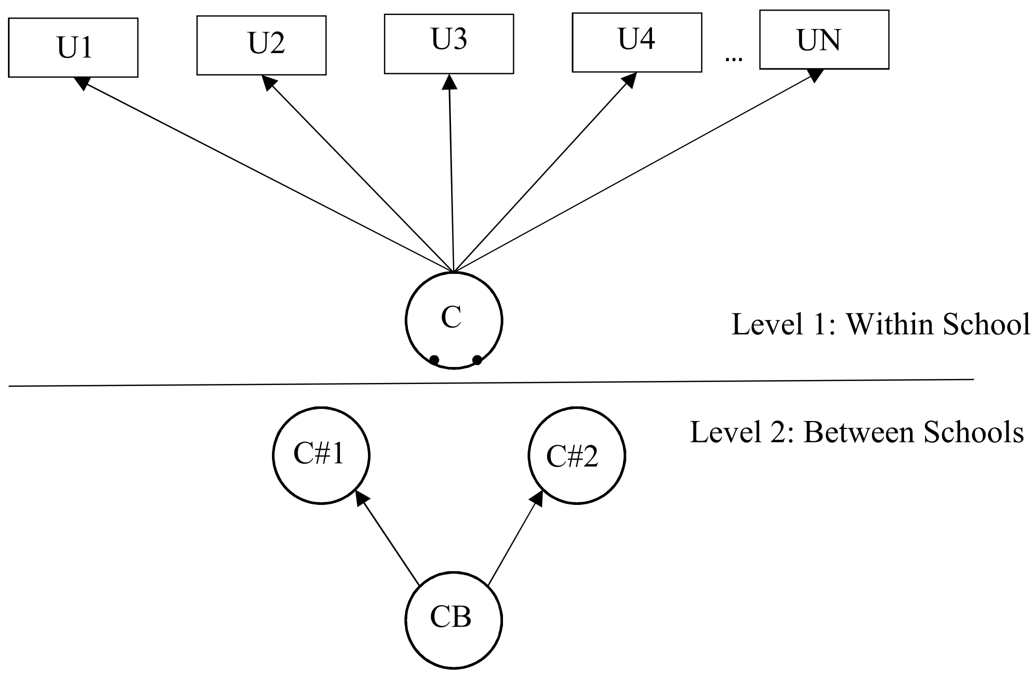

Figure 3.1 *Nonparametric MLPA*
Note. Adapted from Henry & Muthén (2010).

Stage 2: Estimate Unconditional MLPA and Obtain BCH Weights

After the appropriate number of profiles were identified at both the student and school levels in Stage 1, Step 1 of the BCH 3-Step procedure was applied to the resulting non-parametric MLPA model. In this first model run, this model was estimated, and the resulting BCH weights were saved for use in second model run in Mplus. The KNOWNCLASS option was also included to allow for the analysis of profiles and auxiliary variables by school type (elementary, middle, high).

Stage 3: Include Auxiliary Variables

Using the output derived from the first model run outlined above, a second model run was conducted to carry out Steps 2 and 3 of the procedure. Auxiliary variables were

added to the model and BCH weights for each identified profile served as training data by using the TRAINING option. Training data necessitates one variable for each latent profile and each individual receives a value of zero or one for each class variable, indicating exclusion or inclusion from class membership, respectively (Muthèn & Muthèn, 2009). Thus, the latent class variable (class assignment) is transformed into an observed variable that becomes part of the observed likelihood and can be used evaluate the model in the context of auxiliary variables (Muthèn, 2001).

Auxiliary variables can take the form of either covariates or distal outcomes. The current study included a measure of school poverty as a covariate and incorporates college and/or career readiness and academic achievement as distal outcomes. Due to the lack of publicly available student-level data on outcome indicators, distal outcome variables were only evaluated at the school level. Each auxiliary variable is explained in further detail below. Additionally, two distal outcomes could only be analyzed in relation to high school data (career and/or college readiness). To accommodate this issue, the aforementioned KNOWNCLASS option was applied to allow for evaluation of the profiles and distal outcomes across school type.

Poverty. While high poverty levels are generally associated with poorer school climate, a positive school climate can help mitigate the negative impacts of poverty (Bernstein, 1992; DiStefano et al., 2016; Eccles et al., 1993; Hopson & Lee, 2010). The potential impact of poverty on latent profile formation was evaluated by including it as a covariate at the school level. It was measured using South Carolina (SC) Poverty Index data for the 2017-2018 school year. The SC Poverty Index is a composite based on prevalence of student enrollment in programs like Medicaid, Temporary Assistance for

Needy Families (TANF), Supplemental Nutritional Assistance Program (SNAP), and foster care services as well as on migrant or homeless status. The average school poverty index for the state of South Carolina in 2018 was 61.2 out of 100, with higher values indicating increased poverty. Schools ranged in poverty index values of 7.3 to 98 in that same year with a median poverty index of 69.4.

College and/or Career Readiness. College-and-career readiness (CACR) and college-or-career readiness (COCR) were included as a distal outcomes to gain greater insight into the longer-term impacts of school climate on the availability of opportunities beyond the classroom. College/career readiness is reported to meet requirements of both the state and federal accountability systems (South Carolina Department of Education & South Carolina Education Oversight Committee, 2020). While South Carolina only uses COCR as part of each school's accountability rating, this study also includes CACR to add a more rigorous measure of student preparedness, as measures of student achievement fall short if they are not used to further students' college and/or career goals. While SC school climate has been investigated in relation to student achievement, it has not been evaluated in terms of terms of CACR and COCR.

Data for CACR and COCR from 2019 was used to look at high school climate profiles from 2018. This was done because eleventh grade student perceptions measured in 2018 could be relatively connected to the college/career ready indicators collected across twelfth grade students in 2019. In the state of South Carolina, each student receiving a high school diploma between June 16, 2018 and June, 15, 2019 was evaluated based on a set of criteria to determine whether they are career-ready, college-ready, career-or-college ready, and college-and-career ready.

To be college-ready, students were to have a minimum ACT composite score of 20, a minimum SAT composite score of 1020, a score of 3 or higher on any Advanced Placement (AP) exam, a grade of C or higher in any Advanced Level (A) Cambridge International Exam or Advanced Subsidiary (AS) Level Cambridge International Exam in a range of specified subjects (e.g., biology, psychology, economics), a minimum score of 4 on any International Baccalaureate (IB) assessment (higher learning exams only), *or* minimum of six credit hours in approved dual enrollment courses with a grade of C or higher (South Carolina Department of Education & South Carolina Education Oversight Committee, 2019).

To be considered career-ready, students must have completed career and technical education (CTE) program with national/state industry credential as determined by the business community, earned a Silver, Gold, or Platinum national career readiness certificate on WorkKeys or WIN Ready to Work Career assessment, earned a minimum score of 31 on the Armed Services Vocational Aptitude Battery (ASVAB), *or* successfully completed a state-approved work-based learning exit evaluation from an employer (must meet specific guidelines; South Carolina Department of Education & South Carolina Education Oversight Committee, 2019).

Students who met any of the above requirements would be labeled as ‘college or career ready’ by the state of South Carolina. The percentage of COCR students is calculated by dividing the total number of students with this designation by the total number of high school graduates. Points are determined by dividing the percentage of COCR students by four; these values are then converted into Ratings (see Table D.1). Thus, a school where 80% of its students were considered COCR would receiving an

‘excellent’ rating (South Carolina Department of Education & South Carolina Education Oversight Committee, 2019).

Note that for the 2018-2019 school year, percentages were computed based on the total number of CACR and COCR students out of all graduates in that year. However, as of the 2019-2020 school year, the computation of these indicators has changed to allow the entire Grade 9 cohort to serve as the denominator in the calculation of CACR and COCR percentages More information on these indicators can be found on the SC Department of Education webpage (see South Carolina Department of Education & South Carolina Education Oversight Committee, 2019, p.40-41).

Academic Achievement. Favorable school climate is associated with improved student academic achievement (Greenberg, 2004; Lee & Burkham,1996; Stewart 2008). Given this relationship and that a central goal of educational institutions is to improve achievement and learning, it was included as a distal outcome at the school level of the model. Students’ academic achievement also serves as a state and federal accountability measure. Students in Grades 3-8 are evaluated on their academic achievement based on the SC College-and-Career Ready Assessment (SC READY) while students in high school are measured based on the End-of-Course Examination Program (EOCEP).

In elementary and middle school in 2017-2018 school year, students took the SC Ready exam in math and ELA. For each student and test (ELA, math), a maximum of three points can be earned (see Table D.2). Points earned are summed across students for each test. The total number of points earned is calculated as a percentage out of the total number of possible points (maximum points possible multiplied by number of students). Each percentage is then converted to a 40- and 35-point scale for schools without and

with at least 20 ELP students, respectively, and assigned ratings ranging from unsatisfactory to excellent as displayed in Table D.3 (South Carolina Department of Education & South Carolina Education Oversight Committee, 2018).

For high school students, English 1 and Algebra 1 are measured via End of Course Examination Program (EOCEP) scores which are expected to be taken by the end of each student's third year of high school. Each student can earn a total of 4 points that correspond to a letter grade (A-F, see Table D.4). Points earned are summed across students for each test. The total number of points earned is calculated as a percentage out of the total number of possible points (maximum points possible multiplied by number of students). Each percentage is then converted to a 25- and 30-point scale for schools without ELP and with at least 20 ELP students, respectively, and assigned ratings ranging from unsatisfactory to excellent (South Carolina Department of Education & South Carolina Education Oversight Committee, 2018).

It is also important to note the students and/or scores included in each measure. For elementary and middle schools, only students who are enrolled on both the 45th and 160th day of class with no breaks in enrollment are included in the ratings. While students taking the alternative assessments are included, those who are not initially English proficient and/or entered the United States after the 45th day of the prior academic year are excluded. Zero points are assigned for each student who should have taken each subject area test but failed to do so. At the school level, if less than 95% of eligible students are tested, then the school's rating in Academic Achievement will automatically be reduced by one rating level (South Carolina Department of Education & South Carolina Education Oversight Committee, 2018).

For high schools, the highest scores taken at any previous point in time are used for each student. The total number of students measured (denominator) is based on the graduation cohort which includes students who attended the high school within the previous four years and excludes students who transferred, passed away, or emigrated. Also excluded from the denominator were students awarded a transfer credit in Algebra I or English I from accredited schools or home-schools and who entered the United States after the 45th day of the prior academic year. Similar to elementary and middle schools, a school's rating in Academic Achievement was automatically reduced by one rating level when less than 95% of eligible students were tested (South Carolina Department of Education & South Carolina Education Oversight Committee, 2018).

For the current study, the percent of students meeting specific cut-offs for math and English/ELA (here, 'percent met' for elementary and middle schools and percent receiving an A-C designation for high school) within each school served as indicators of academic achievement at the school level.

Alternative Analysis Plan

Unforeseen problems pertaining to the proper implementation of aforementioned analysis plan resulted in the creation of an alternate plan of action. While the unconditional LPA and nonparametric MLPA models were estimated successfully, errors occurred when attempting to complete Step 1 of the BCH 3-Step procedure for the nonparametric MLPA model. Specifically, BCH weights could not be estimated when using a two-level mixture model in Mplus.

As a result, the unconditional LPA and nonparametric MLPA models were estimated to identify student- and school-level profiles. A parametric unconditional LPA

model was also estimated to evaluate school climate data at the school level. School-level averages were computed for each item and the resulting dataset was used to identify the appropriate number of profiles at the school level. This unconditional model was then incorporated into the manual BCH 3-Step procedure using the auxiliary variables outlined in the previous section. The absence of auxiliary variables at the student level precluded the use of the BCH 3-Step procedure with student-level data.

It is acknowledged that use of this alternative plan is not ideal in terms of limiting biased and imprecise parameter estimates. However, proper implementation of the original model was not possible given the constraints of the modeling software. This analysis plan will serve as an intermediary step towards full implementation once the software has the capacity to estimate the original model using the manual BCH 3-step method.

Summary

The goal of this chapter was to present a clear and guided review of the methods used in this study. Model assumptions and estimation procedures involved in the manual BCH 3-Step approach presented alongside an examination of each step in the context of the current study. Difficulties in completing the proposed analysis plan were identified and an alternative plan for analysis was presented. Results emanating from the methodological procedures carried out in this study and how they can inform future work will be discussed in Chapter 4 and Chapter 5.

CHAPTER 4

RESULTS

The purpose of the chapter is to present the results yielded by the alternative BCH 3-Step procedure outlined in Chapter 3. This procedure was adopted due to the inability of the software to carry out the necessary procedures for a *multilevel* mixture model using the BCH 3-Step approach. This chapter is divided into two main sections. Per the original analysis plan, the first focuses on the results of the student-level unconditional LPA model that was conducted when identifying the number of lower-level profiles for inclusion in the non-parametric MLPA. The second section focuses on an application of the BCH 3-Step to the school-level dataset. Within this section are the examination of school-level unconditional LPA models and the integration of the most appropriate model into the BCH 3-step procedure. Results of the BCH 3-Step approach as it is applied to the school-level LPA will then be presented.

Student-Level LPA

Latent profile analysis was conducted to test models containing one to six profiles. These models are hereafter referred to as Lower-Level Models one through six (LLM 1-6). Models were compared based on their absolute and relative fit, classification diagnostics, profile proportions, and item-level comparisons (within and across school climate factors) to arrive at the most appropriate model. The following sections present a detailed view of the findings within each of these components.

Fit Indices

Models were examined and compared using both overall and relative fit indices. Results pertaining to overall model fit are provided in Tables 4.1 and 4.2. The absolute and relative fit indices presented in Table 4.1 suggest that LLM6 has superior fit because it has the highest values for the Log Likelihood (LL) index and because significant p-values occur up to six profiles for LMR-LRT and LMR-aLRT. The information criterion shown in Table 4.2 also support the selection of a six-profile model with the lowest values of AIC, BIC, aBIC, and AWE occurring within LLM6. Though, values for all indices were very similar across models.

The six-class model yielded optimal fit based on statistical indices, however, it is important to note that model fit will typically improve as profiles are added to a model. For this reason, values of these fit indices should not be the sole determinant in choosing the most appropriate model. Further, "elbow" plots of these indices can often prove useful in identifying where the largest gains/drops in fit occur. Values are compared across models using a line graph. When slope of the line lessens, from one model to the next, it can create a noticeable bend, or "elbow", in the plotted line. This bend suggests that additional classes may not be needed. For example, the greatest gains in LL occurred as a second profile is added to a one-profile model.

Table 4.1 *Absolute and relative fit indices for lower-level LPA models*

Model	LL[a]	LMR-LRT	LMR-aLRT
LLM1	-6251732.581		
LLM2	-5873646.894	-6251732.580*	754,340.560*
LLM3	-5762570.590	-5873646.890*	221,614.740*

LLM4	-5717902.311	-5762570.590*	89,120.260*
LLM5	-5676315.987	-5717902.311*	82,971.270*
LLM6	-5651746.041	-5676315.987*	49,020.920*

Note. Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) and adjusted Lo-Mendell-Rubin Likelihood Ratio Test (LMR-aLRT) do not apply to LLM1

[a] Significance values are not applicable to Log likelihood (LL) values.

*$p<0.05$.

Table 4.2 *Information criterion for lower-level LPA models*

Model	AIC	BIC	aBIC	AWE
LLM1	12,503,601.163	12,504,265.666	12,504,049.559	12,503,914.816
LLM2	11,747,499.788	11,748,506.315	11,748,178.978	11,747,974.882
LLM3	11,525,417.180	11,526,765.730	11,526,327.163	11,526,053.713
LLM4	11,436,150.620	11,437,841.200	11,437,291.395	11,436,948.595
LLM5	11,353,047.970	11,355,080.570	11,354,419.541	11,354,007.387
LLM6	11,303,978.080	11,306,352.710	11,305,580.442	11,305,098.934

Note. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted Bayesian Information Criterion (aBIC), Approximate Weight Evidence Criterion (AWE)

The largest changes for LMR-LRT and LMR-aLRT values occurred when progressing from LLM2 to LLM3, albeit the change was noted in opposite directions (see Figure E1 in Appendix E). For information criterion used to further assess relative model fit, the largest decreases typically occurred between LLM1 and LLM2 (see Figure E.2 in

Appendix E). Thus, contrary to what was suggested by the *values* of the fit indices, the elbow plots suggested the selection of a two- or three-profile model.

Classification Diagnostics

Entropy and average latent class probabilities were also examined to evaluate the quality of each model. Each is discussed in detail below.

Entropy. Entropy, a measure of profile separation, was also examined across each of the six models (see Table 4.3). The one- and two-profile models displayed the highest levels of entropy at 0.923 and 0.902, respectively, indicating clearer distinctions of individuals across their assigned latent profiles. Entropy was not evaluated for LLM1 because only one profile was modeled.

Table 4.3 *Entropy for lower-level LPA models*

Model	Entropy
LLM1	
LLM2	0.923
LLM3	0.902
LLM4	0.883
LLM5	0.883
LLM6	0.865

Note. Entropy cannot be calculated for a one-profile model.

When comparing values for LLM4-LLM6, entropy was highest in in the models with four and five profiles (0.883) compared to the model with six profiles (0.865). Entropy declines most sharply between LLM2 and LLM3 (decrease of 0.012). It then plateaus between LLM4 and LLM5 and declines slightly by 0.018 when adding a sixth

profile in LLM6. Values of entropy are graphed across models in Figure E.3 in Appendix E.

While there were declines in entropy from LLM2 to LLM6, they were not considered to be substantial enough to warrant the exclusion of the four-, five-, and six-profile models. Further, the classification of individuals into profiles is considered to be "good" when the values of entropy are greater than 0.80 (Clark & Muthèn, 2009; Nylund-Gibson & Choi, 2018, p.14).

Average Posterior Probabilities. Within each subset of student observations that are most likely to be assigned to a given profile, the posterior probabilities for each profile were averaged, creating a value known as the average (latent class) posterior probability, or AvePP (see Table 4.4).

Table 4.4 *Average posterior probabilities by profile for lower-level LPA models*

Model	Profile					
	1	2	3	4	5	6
LLM2	0.966	0.984				
LLM3	0.954	0.949	0.960			
LLM4	0.953	0.928	0.926	0.938		
LLM5	0.961	0.902	0.915	0.932	0.919	
LLM6	0.961	0.906	0.918	0.852	0.854	0.951

All AvePP values across all models were markedly above the recommended minimum of 0.70 (Nylund-Gibson & Choi, 2018). For LLM2, the average posterior probability for students assigned to Profile 1 is 0.966. The highest AvePP of 0.984 occurred within LLM2 for students assigned to Profile 2. The lowest AvePP values of

0.852 and 0.854 occurred in LLM6 for Profiles 4 and 5, respectively. Though, the average probability values for the remining profiles in LLM6 were all at or above 0.906.

Profile Proportions

The proportion of students assigned to each lower-level profile was also examined for each model. Table 4.5 depicts the final class counts and proportions for each latent profile based on their most likely class membership. In a two-profile model, approximately 34% of students were assigned to Profile 1 while the remaining 66% were assigned to Profile 2.

As profiles were added, profile proportions decreased in size. In LLM6, the lowest proportion occurred in Profile 1 which represented roughly 4% of all students in the sample. The value of each profile, however, was not purely dependent on its size and was also determined by item-level information (which is discussed in the following section).

Table 4.5 *Final Class Counts and Proportions for Lower-Level LPA Models*

Model	Profile	Count	Proportion
LLM 2	1	43,557	0.336
	2	86,030	0.664
LLM 3	1	15,176	0.117
	2	56,686	0.437
	3	57,725	0.445
LLM 4	1	5,358	0.041
	2	26,672	0.206
	3	54,762	0.423
	4	42,795	0.330
LLM 5	1	5,892	0.045
	2	21,246	0.164

Model	Profile	Count	Proportion
	3	50,942	0.393
	4	39,014	0.301
	5	12,493	0.096
LLM 6	1	4,871	0.038
	2	16,533	0.128
	3	10,868	0.084
	4	26,286	0.203
	5	27,579	0.213
	6	43,450	0.335

Item Estimates by Profile

Item-level estimates across profiles were examined for the three models with the best fit (LLM4, LLM5, and LLM6). Estimates were grouped by factors identified via EFA and CFA procedures (learning environment, social/physical environment, home-school relationship, and safety) and compared across models. Item means, standard errors, and statistical significance values for each of these three models is presented in Appendix F. Because item labels changed and new factors were assigned for the analysis, an item-factor guide is provided in Appendix G to allow for ease of interpretation.

After a careful review of each model in conjunction with the aforementioned findings, LLM6 was selected to be the most appropriate model for the current study. Reasons behind this selection are discussed below. Item-level graphs by factor for LLM6 are displayed in Figures 4.1-4.4. Similar graphs for LLM4 and LLM5 can be found in Tables H.1-H.8 in Appendix H. Note that the item values presented in each graph are in

the standard deviation form. Thus, an item value of -1, for example, indicates that the value is one standard deviation *below* the mean.

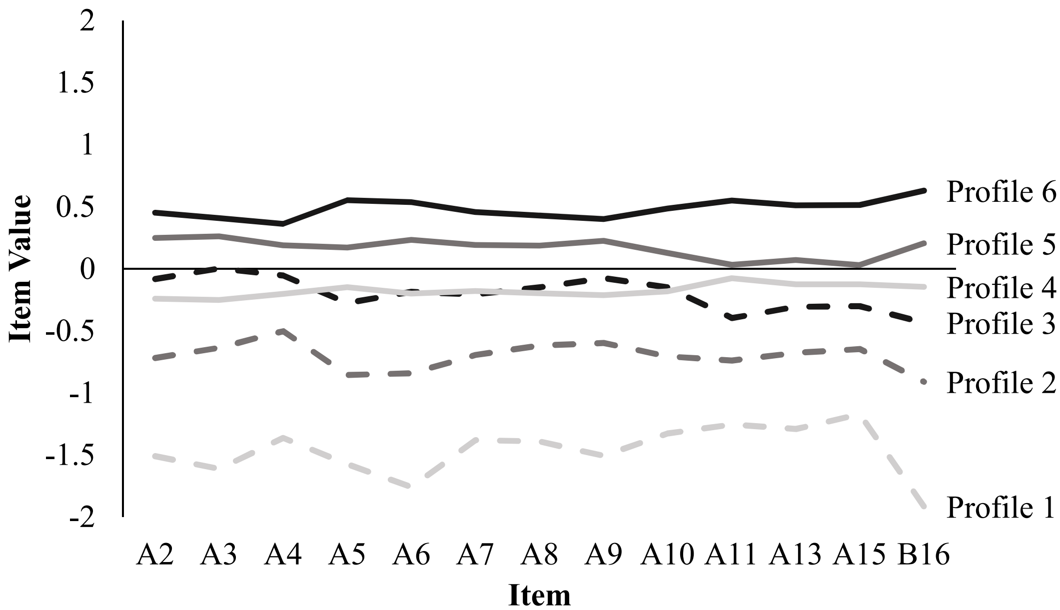

Figure 4.1 *Learning Environment Domain, Six-Profile Model*

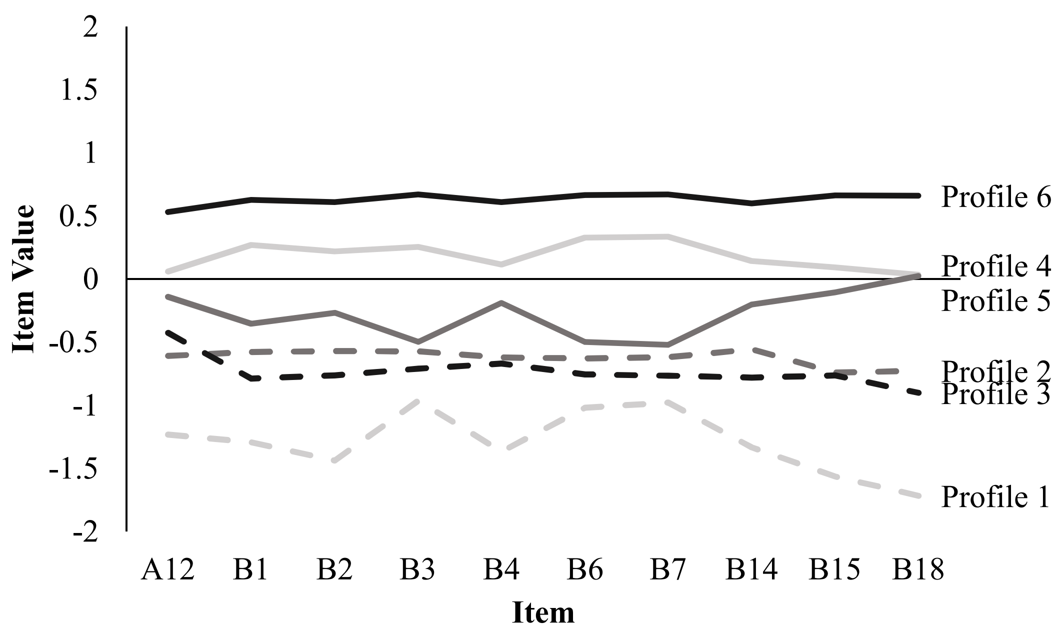

Figure 4.2 *Social/Physical Environment Domain, Six-Profile Model*

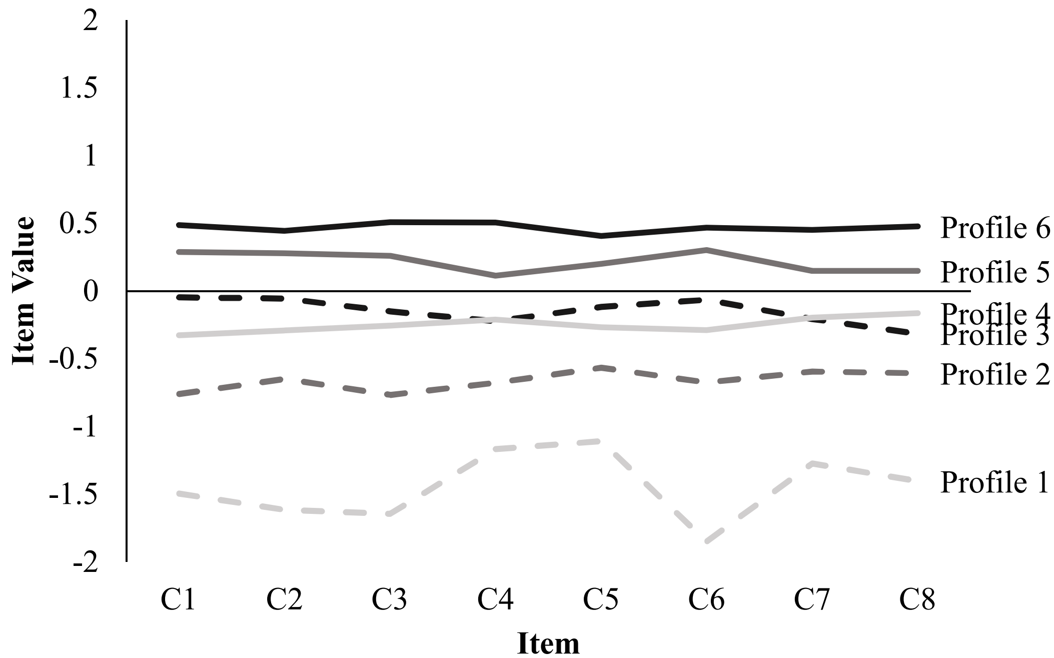

Figure 4.3 *Home-School Relationship Domain, Six-Profile Model*

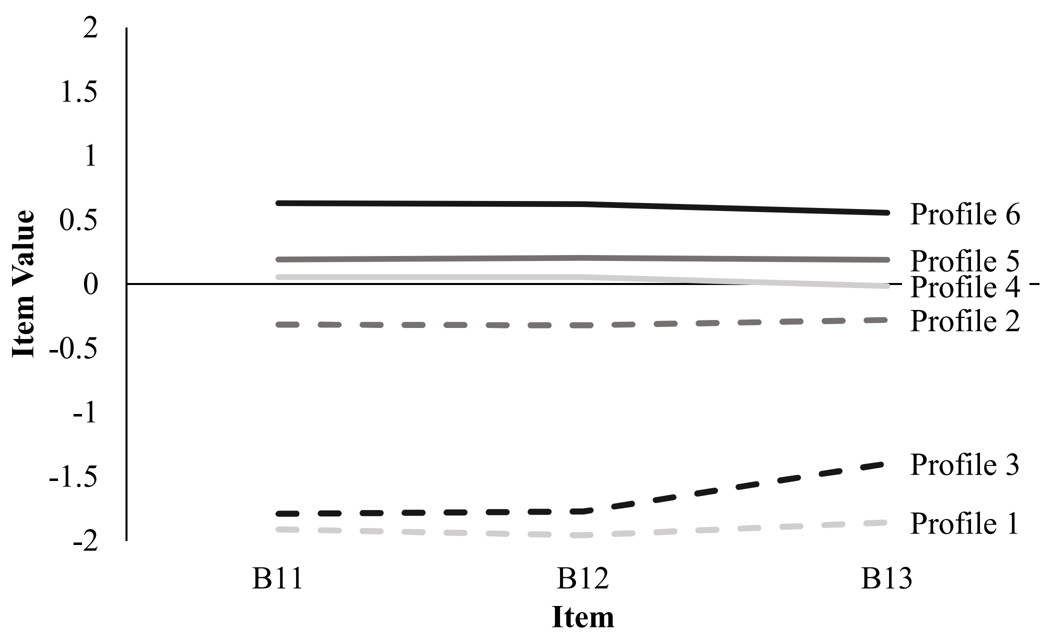

Figure 4.4 *Safety Domain, Six-Profile Model*

In LLM6, the lowest item values present in Profile 1, ranged from -1.955 (Item B12, "I feel safe at my school during the school day.") to -0.961 (Item B3, "The

bathrooms at my school are kept clean."). Values for Profile 2 are slightly higher than Profile 1, on average, but remain negative. Profile 3 has several item values that are very low similar to Profile 1 (particularly B11-B13 which safety-related items), but the remaining values are more positive than all of those in Profiles 1 and 2. Item values for Profiles 4 and 5 hover around the mean of zero, but alternate on which items present as positive or negative. Finally, item values in Profile 6 are all positive, albeit most are not larger than 0.60.

In LLM4, profiles could generally be categorized as low, below-average, average, and above-average school climate. In LLM5, Profile 3 emerged (similar to Profile 3 in LLM6) which provided a wider range of negative and positive values (-1.635 to .024) compared to the other profiles. The alternating high and low values across items in Profiles 3 and 4 (i.e., items high in Profile 4 were low in Profile 3 and vice versa) solidified LLM6 as the preferred model, as these patterns did not exist in LLM4 and LLM5 and could help to further pinpoint specific types of students in schools as it relates to school climate.

Item Estimates by Factor for Selected Model

For the selected six-profile model, patterns of low, average, and above average climate remained relatively stable across school climate factors with a few exceptions. For Learning Environment (see Figure 4.1), Profile 1 had the lowest values for all items, with the highest and lowest items being A15 ("The textbooks and workbooks I use at my school really help me to learn.") and B16 ("Teachers work together to help students at my school."), respectively. Profile 2 had the second-lowest values for all items. Seven item values (A2-A4, A6, and A8-A10) for Profile 3 were higher than Profile 4 while others

were equal or lower in value. The highest values were in Profile 6 followed by Profile 5 for all items. The highest values for Profile 5 and Profile 6 were A3 ("My teachers expect students to learn") and B16 ("Teachers work together to help students at my school."), respectively. The lowest value for Profile 5 was A15 ("The textbooks and workbooks I use at my school really help me to learn.") while the lowest value for Profile 6 was A4 ("My teachers expect students to behave.").

Looking to Social-Physical Environment in Figure 4.2, similar patterns persisted, where Profile 6 displayed the highest item values. However, Profile 4 item values are now higher than Profile 5, and Profile 2 now displays higher values than Profile 3 for most items. The values for Profile 1 remain the lowest across all items within the factor.

Item patterns under the Home-School Relationship factor generally reflected those present under Learning Environment across all profiles (see Figure 4.3). Five of the eight items were higher in Profile 3 than in Profile 4 (C1-C3, C5-C6). Also, similar to the aforementioned factors, Profile 1 displayed the most erratic item values within the factor for Home-School Relationships (though, as will be discussed later, Profile 3 and Profile 1 have the largest range of item values when looking across all items).

The items related to the Safety factor presented in Figure 4.4 displayed the least amount of variation compared to the others with values remaining fairly constant within profile for Profile 2 and Profiles 4-6. Profile 1 and Profile 3 displayed similar values for B11 ("I feel safe at my school before and after school hours.") and B12 ("I feel safe at my school during the school day."), but higher values for B13 ("I feel safe going to or coming from my school.") were present in Profile 3. Within the Safety factor, B13 was the highest-value item for Profiles 1-3 but the lowest-value item for Profiles 4-6.

Examining patterns within and across profiles.

The relative positions and scales of items and factors within each profile were also analyzed to get a deeper understanding of the structure of each profile. Results from this process were used to create profile names and non-numeric descriptions believed to be more appropriate to lay and policy-oriented audiences.

At the start of this process, items were ranked from highest to lowest within each profile and labeled with the name of their respective factor (see Figures I.1 – I.6 in Appendix I). The positions of items and factors as well as the span of their values were then compared within and across profiles. A summary of the findings from this comparative process is presented below in Table 4.6.

Looking *across* profiles, it was clear that Profile 1 and Profile 6 could be categorized as having critically low school climate and above-average school climate, respectively. The majority of item values in Profile 1 are over one standard deviation below the mean with several close to two standard deviations below the mean. Profile 4 and Profile 5 can be considered to have average school climate. Most items in Profile 5 fall between 0 and 0.3 standard deviations above the mean, with nine items under SPE factor falling below the mean with the lowest value at -0.521. Item patterns in Profile 4 appear to be the inverse of Profile 5 in that all items range between -0.3 and 0.3 standard deviations from the mean with the most positive values occurring within the SPE factor.

Profiles 2 and 3 are classified as having below-average climate. These profiles vary mostly in the range of their item values. Items in Profile 2 are relatively uniform in value (ranging from -0.909 to -0.277) compared to those in Profile 3 (-1.788 to 0.004).

The relative positions of items/factors were then identified *within* each profile and compared across profiles as a means of pinpointing how they varied not only in degree but in content. For example, students in Profile 1 seem to think very poorly of school climate in terms of safety (SA) compared to other factors, as all of the safety items have the lowest values. Among the least negative values are items within the SPE, HSR, and LE factors. Those with the highest values are three SPE items related to bathroom cleanliness (B3), student behavior within class (B6), and student behavior outside of class (B7) that are almost a full standard deviation above the lowest-value item under the SA factor (B12, "I feel safe at my school during the school day."). Students in Profile 1 were labeled to have ***'Very low climate and safety'***.

Looking to Profile 6, with the highest item values across all profiles, it is interesting that items within SPE have the highest values similar to Profile 1. However, while safety was a concern for Profile 1, Learning Environment and Home-School Relationships have the lowest values for Profile 6. However, because all of these values are still-above average and higher than those in any other profile, it seems inappropriate to list that as a concern for this profile. For this reason, students in Profile 6 were designated as having ***'High climate'***.

Profile 5 and Profile 4 were both categorized as 'average' when looking across profiles given that most of the items within them hovered around the mean. However, Profile 5 displays positive values for all items except those within the SPE factor. In Profile 4, the vast majority of positive items fall within the SPE factor and the lowest items are under the HSR and LE factors. Thus, students in Profile 5 were labeled to have ***'Average climate and low social-physical environment'*** and students in Profile 4 were

Table 4.6. *Within- and Across- Profile Comparisons*

Profile (%)	Name	Analysis level		Descriptive label
		Within profiles	Across profiles	
1 (3.8%)	Very low climate and safety	Relatively high SPE and extremely low SA, HSR, and LE	Lowest on all items and factors	Critically low climate with concerns for safety
2 (12.8%)	Low climate, low LE	Relatively high SA and low LE, and HSR	Higher than Profile 3 in SPE and SA but lower in LE and HSR	Below-average climate with concerns for learning environment
3 (8.4%)	Low climate, low SPE-SA	Low SPE and extremely low SA	Higher than Profile 2 in LE and HSR but lower in SPE and SA	Below average climate with concerns for social-physical environment and critical concerns for safety
4 (20.3%)	Average climate, low HSR-LE	Relatively high SPE, medium SA, and low HSR and LE	Values slightly above/below zero and lower than Profile 5 except in SPE	Average climate with concerns for home-school relations and learning environment

Profile (%)	Name	Analysis level		Descriptive label
		Within profiles	Across profiles	
5 (21.3%)	Average climate, low SPE	Low SPE and relatively high HSR, LE, and SA	Values slightly above/below zero and higher than Profile 4 except in SPE.	Average climate with concerns for social-physical environment
6 (33.5%)	High climate	Relatively high SPE Above average LE, SA, HSR	Highest on all items and factors	Above average climate with no immediate causes for concern

considered to have ***'Average climate and low home-school relations and learning environment'***.

Looking to Profile 2 and Profile 3, both were labeled as having below-average climate when looking across profiles. Looking within profiles, all items within Profile 2 ranged between -0.277 and -0.909 with SA items possessing the highest values and LE items having the lowest values. Students in this profile were labeled as having ***'Low climate and learning environment'***. For Profile 3, items ranged between 0.004 and -1.914 standard deviations below the mean. While the majority of HSR and LE items were within half a standard deviation below the mean, most SPE items were within half- to a full-standard deviation below the mean and all SA items were 1.396 to 1.788 standard deviations below the mean. For this reason, students assigned to Profile 3 were classified as having perceptions of ***'Low climate and social-physical environment with very low safety'***.

On balance, the differences within and across each of the six selected latent profiles provided a deeper look into the varied views of school climate among students in South Carolina. While one could argue that a model with fewer profiles is more appropriate in the current context, the decision to select six profiles was based not only on model fit but a subjective evaluation of item patterns within and across profiles. This evaluation illuminated patterns that may otherwise have been lost if these profiles were subsumed within profiles that were more general and fewer in number. The subjective and contextual nature of selecting the 'most appropriate' profile will inevitably lead to disagreements among researchers about what is and is not appropriate—an issue that will be explored further in Chapter 5.

School-Level LPA

To arrive at the appropriate number of upper-level profiles, LPA was conducted for models containing one to four profiles. The nonparametric MLPA conducted prior to adopting the alternative analysis plan suggested the existence of three profiles. Thus, an analysis of up to four profiles seemed appropriate. The four examined models will hereafter be referred to as Upper-Level Models one through four (ULM1-4), with the number indicating the quantity of profiles included within a given model. Recall that data used in these analyses reflect school-level averages across standardized student survey item responses.

Fit Indices

Results pertaining to model fit are provided in Tables 4.7 and 4.8. The relative fit indices presented in Table 4.7 suggest that ULM2 has superior fit. While the log likelihood value was highest for ULM4, the largest improvements in absolute fit occurred when progressing from a two- to three-profile model (See Figure J.1 in Appendix J). Further, only ULM2 values for LMR-LRT and LMR-aLRT were statistically significant ($p < 0.05$), suggesting that a model with two profiles was sufficient.

Looking at information criteria to further inform relative fit in Table 4.8, ULM4 displayed the best fit across all indicators with the lowest values for AIC, BIC, aBIC, and AWE. The sharpest drop in information criteria indicators, however, occurred when advancing from a one- to two-profile model (See Figure J.2 in Appendix J).

Table 4.7 *Absolute and relative fit indices for upper-level LPA models*

Model	LL[a]	LMR-LRT	LMR-aLRT
ULM1	-547.119		

Model	LL[a]	LMR-LRT	LMR-aLRT
ULM2	5,883.469	-547.119*	12,808.372*
ULM3	8,789.430	5,883.469	5788.060
ULM4	10,227.563	8,789.430	2,864.457

Note. Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) and adjusted Lo-Mendell-Rubin Likelihood Ratio Test (LMR-aLRT) do not apply to LLM1.

[a] Significance values are not applicable to Log likelihood (LL) values.

*Statistically significant ($p<0.05$).

Table 4.8 *Relative fit indices for upper-level LPA models*

Model	AIC	BIC	aBIC	AWE
ULM1	1,230.237	1,565.511	1,349.536	1,400.910
ULM2	-11,560.938	-11,053.097	-11,380.236	-11,302.420
ULM3	-17,302.860	-16,622.452	-17,060.753	-16,956.500
ULM4	-20,109.125	-19,256.150	-19,805.615	-19,674.920

Note. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted Bayesian Information Criterion (aBIC), Approximate Weight Evidence Criterion (AWE).

Classification Diagnostics

Entropy and average latent class probabilities were also examined to evaluate the quality of each model. Each is discussed in detail below.

Entropy. The values for entropy improved as the number of profiles increased across models (see Table 4.9 and Figure J.3). While ULM3 and ULM4 shared the highest entropy value (0.962), ULM2 was only slightly lower at 0.954. It is interesting that while

entropy decreased with the introduction of additional profiles in the lower-level model, it increases here (albeit, minimally) with the addition of profiles at the school level.

Table 4.9 *Entropy for upper-level LPA models*

Model	Entropy
ULM1	
ULM2	0.954
ULM3	0.962
ULM4	0.962

Note. Entropy not applicable for a one-profile model.

Average Posterior Probabilities. Within each subset of school-level observations that are most likely to be assigned to a given profile, the posterior latent class probabilities for each profile are averaged, as shown in Table 4.10. All values range between 0.973 and 0.996, with the lowest and highest values residing in ULM4 for Profile 2 and Profile 4, respectively.

Table 4.10 *Average posterior probabilities by profile for upper-level LPA models*

Model	Profile			
	1	2	3	4
ULM2	0.984	0.988		
ULM3	0.975	0.986	0.982	
ULM4	0.976	0.973	0.985	0.996

Profile Proportions

The proportion of students assigned to each lower-level profile was also examined for each model. Table 4.11 depicts the final profile counts and proportions for each latent profile based. In ULM2, schools are pretty evenly divided with approximately 50% of

schools assigned to each category. With three upper-level profiles, proportions for one class are halved while the remaining profile remains at 50%. In the final model, ULM4, proportions range from roughly 11% to 40% with Profile 1 and Profile 2 being noticeably larger in size than Profile 3 and Profile 4.

Table 4.11 *Final profile counts and proportions for upper-level LPA models*

Model	Profile	Count	Proportion
ULM 2	1	518	0.50635
	2	505	0.49365
ULM 3	1	266	0.26002
	2	521	0.50929
	3	236	0.23069
ULM 4	1	405	0.39589
	2	327	0.31965
	3	179	0.17498
	4	112	0.10948

Item Estimates by Profile

Item-level estimates across upper-level profiles were examined for ULM2-ULM4. Estimates were grouped by each factor identified via EFA and CFA procedures (learning environment, social/physical environment, home-school relationship, and safety) and compared across models. See Appendix K for item means, standard errors, and statistical significance values for each of these three models.

After a careful review of model estimates in conjunction with the aforementioned findings on model fit and entropy, ULM2 was selected to be the most appropriate model for the current study. Even though several fit indices and entropy supported the selection of ULM3 or ULM4, the analysis of item estimates across all models revealed minimal

profile variation (most within half a standard deviation of the mean) that was exacerbated as profiles were added. Graphs for item estimates by profile and factor for ULM2 are displayed in Figures 4.5-4.8. Similar graphs for the ULM3 and ULM4 can be found in Figures L.1-L.8 in Appendix L.

Two profiles are presented in ULM2 which can best be categorized as above- and below-average climate. Item values for Profile 1 are higher than those for Profile 2 across every factor, though the largest difference between profiles occurs within the factor for Social/Physical Environment. In the three-profile model (ULM3), all item values for Profile 2 were statistically insignificant and near zero across all factors.

When adding a fourth profile to create ULM4, Profile 2 from ULM3 seemingly split into two profiles that were slightly above and below zero (Profile1 and Profile 2) while the remaining profiles came in slightly above/below the original two profiles from ULM2. Again, recall that profile designations are not consistent across models. For example, the students within Profile 1 may differ between ULM2 and ULM4. The assignment of profile numbers is arbitrary and varied across each model estimation procedure.

Item Estimates by Factor for Selected Model.

For the selected two-profile model, patterns of below- and above-average climate remained stable across school climate factors. For Learning Environment (see Figure 4.6), the item with the lowest value was B16 (-0.153, “Teachers work together to help students at my school.”) for Profile 2 and A9 (0.092, “My teachers give tests on what I learn in class.”) for Profile 1.

Interestingly, the item with the lowest value for Profile 2 was also the highest-value item within Learning Environment for Profile 1 (B16, 0.157) while the highest-value item for Profile 2 was A15 (-0.013, “The textbooks and workbooks I use at my school really help me to learn.”). Items closest in value across profiles included A15, A10 (“My teachers give homework assignments that help me learn better.”), A8 (“My teachers do a good job teaching me English language arts.”), and A2 (“My teachers want me to understand what I am learning, not just remember facts.”), with differences ranging from 0.106 to 0.199. Items B6 (“Students at my school behave well in class.”), A5 (“My teachers spend enough time helping me learn.”), and A6 (“My teachers help students when they do not understand something.”) exhibited the largest gaps in values across profiles.

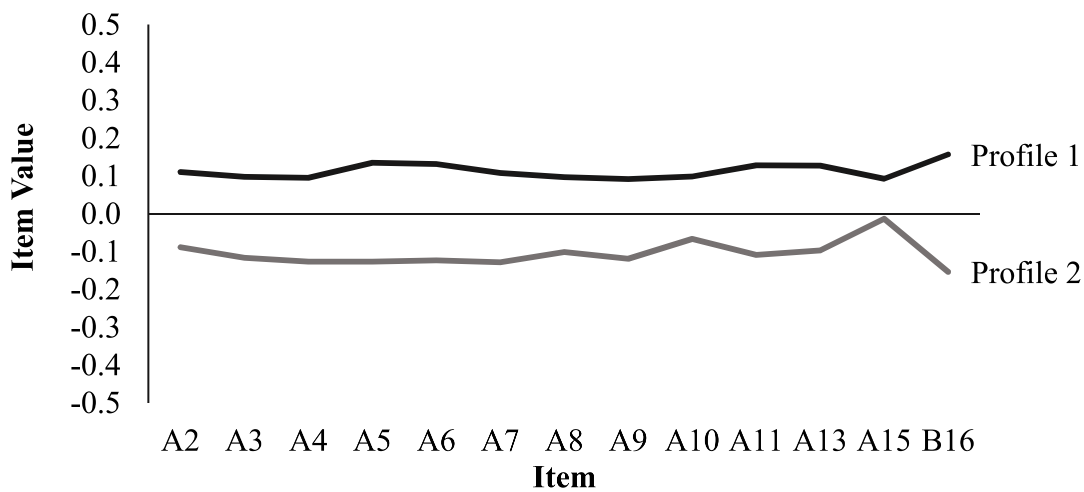

Figure 4.5. *Learning environment factor, upper-level LPA model*

Looking to the Social/Physical Environment factor, items A12 (“Students at my school believe they can do good work.”) and B1 (“The grounds around my school are kept clean.”) have the highest (-0.130) and lowest (-0.259) values, respectively, for Profile 2. In Profile 1, the lowest value was observed for item A12 (0.149) while the

highest value-item was B3 (0.254, “The bathrooms at my school are kept clean.”). Profiles were most similar in their responses to item A12 (difference of 0.279, “Students at my school believe they can do good work.”) and most dissimilar in their response to items B3 and B1 (differences of 0.498 and 0.493, respectively)

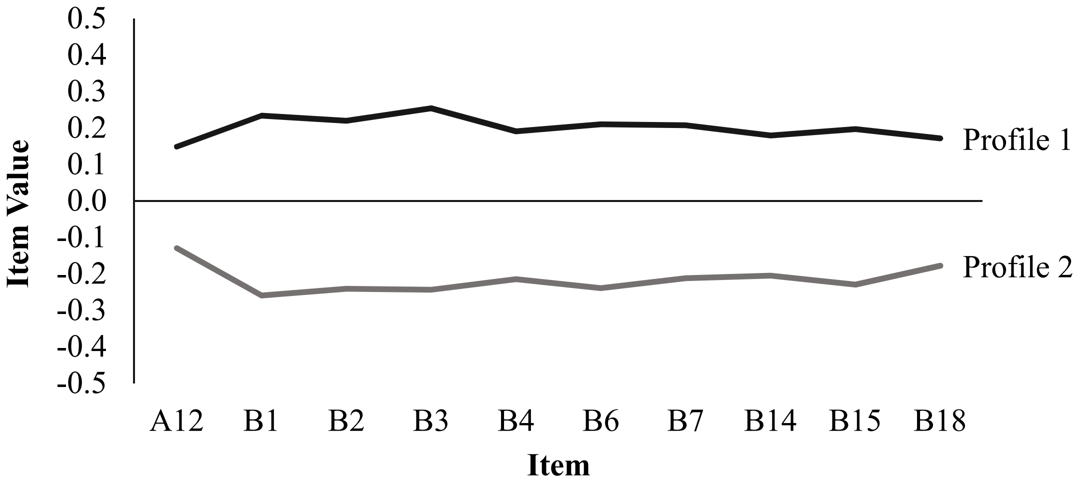

Figure 4.6. *Social/physical environment factor, upper-level LPA model*

Within the Home-School Relationship factor, the lowest items for Profile 2 and Profile 1 were C7 (-0.136, “Parents volunteer and participate in activities at my school.”) and C5 (0.076, “My parent helps me with my homework when I need it.”), respectively. The item with the highest value in Profile 2 was C5 (-0.071), while C3 (“My school informs parents about school programs and activities.”) had the highest value within Profile 1 (0.118). Item value differences between profiles ranged from 0.147 and 0.250, with the smallest difference observed for item C5 and the largest difference existing for item C7.

Finally, items within the Safety factor were the most similar of any items within a factor with differences ranging from 0.306 (B13, “I feel safe going to or coming from my school.”) to 0.374 (B12, “I feel safe at my school during the school day.”). The highest-

and lowest-value items for Profile 2 were B13 (-0.161) and B12 (-0.196), respectively. These same items were the lowest- and highest-value items for Profile 1 (B13=0.145, B12=0.178).

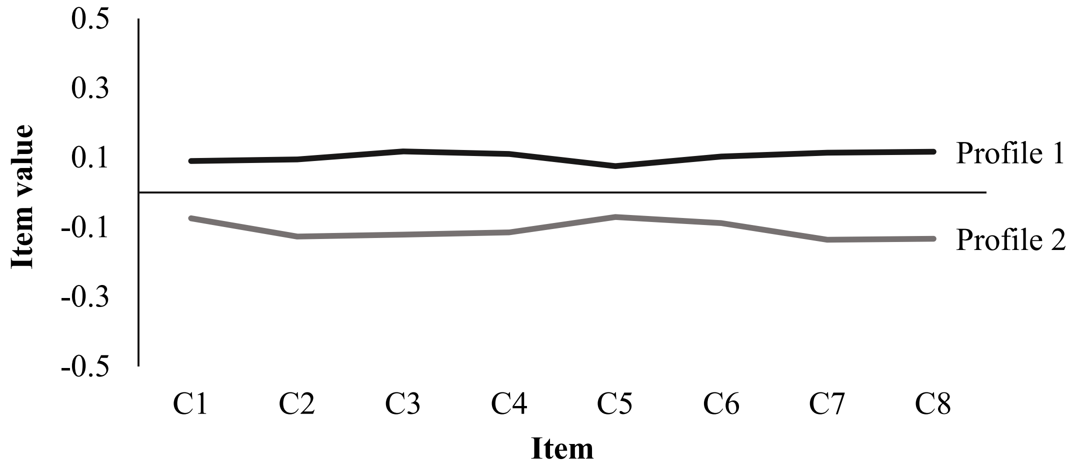

Figure 4.7 *Home-school relationship factor, upper-level LPA model*

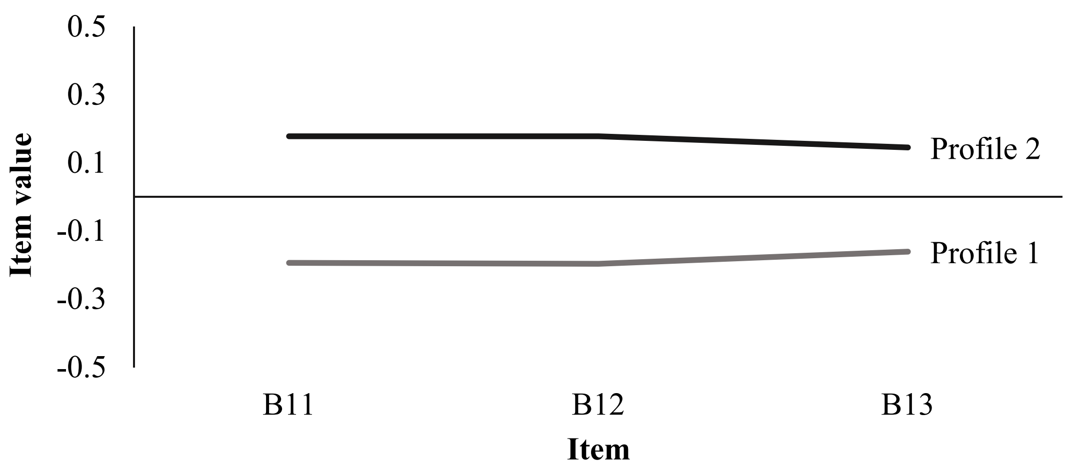

Figure 4.8 *Safety factor, upper-level LPA model*

School-Level BCH 3-Step

The identification and analysis of the unconditional model allowed for the completion of the manual BCH 3-Step procedure. Results obtained from this procedure

are documented in the current section. Considerations regarding model estimation procedures and model selection are examined first. This is followed by results pertaining to profile composition and identification. Auxiliary variables and their relationships with identified profiles are then examined.

Selecting the best model

As discussed in Chapter 3, assumptions related to homogeneity of variance and local independence should be considered when estimating mixture models. While considered, allowing item variances and covariances to be freely estimated was deemed to be unfeasible given the very large sample size and number of items. Allowing items to covary prompted 561 item-item combinations to be estimated. While TECH11 (an Mplus-specific output request) would have proven a useful asset to identify significant covariances to include in the model, it is not available for continuous indicators. As a result, the attempt to incorporate all of these freed parameters resulted in the inability of Mplus to complete the model estimation process for the student-level model. It was concluded that similar issues would occur for the school-level model.

However, an attempt was made to allow covariances of distal outcomes to vary across profiles identified within the manual BCH 3-Step procedure. Two models were examined. Model BCH2a held covariances fixed across profiles. Model BCH2b freed all covariances for Profile 5 and Profile 6 and covariances for "ENG with Math" for remaining profiles. This pattern of fixed and freed parameters was selected because Profiles 1-4 were at the elementary and middle school levels, making any covariances including COCR and CACR immaterial.

Model BCH2b was selected for interpretation due to its provision of class-specific information regarding relationships between distal outcomes, despite its slightly higher values for BIC and aBIC compared to BCH2a (see Table 4.12). Information obtained from this model related to identified profiles and auxiliary variables will be examined in subsequent section.

Table 4.12 *Fit measure values across considered models*

Measure	Model	
	BCH2a	BCH2b
LL	-9,771.997	**-9,747.170**
AIC	19,719.995	**19,700.341**
BIC	**20,153.792**	20,208.081
aBIC	**19,874.296**	19,880.943

Note. Values in bold indicate better fit.

Profile identification and composition

A total of six school-level profiles were identified using the manual BCH 3-Step approach. The addition of the 'KNOWNCLASS' option permitted the inclusion of three 'known classes' to the model based on school level (elementary, middle, and high school). This addition resulted in the creation of six total classes where each of the two latent profiles (high and low school climate) were identified within each school level.

A description of each of the identified profiles along with their respective frequencies and proportions are presented in Table 4.13. Elementary schools (Profiles 1 and 2) made up over 57% of the sample while middle schools (Profile 3 and 4) and high schools (Profiles 5 and 6) represented approximately 23% and 19% of the sample, respectively. Within each school level, high and low climate designations were uniformly

distributed. For example, roughly 49% of the elementary schools were designated as having high school climate while the remaining 51% were designated as having low school climate.

Table 4.13 *Profiles identified using the BCH 3-step procedure*

Profile	Description	Count	Proportion
1	Elementary school, high climate	289	0.283
2	Elementary school, low climate	299	0.293
3	Middle school, high climate	128	0.125
4	Middle school, low climate	109	0.107
5	High school, high climate	100	0.098
6	High school, low climate	97	0.095

Auxiliary Variable Descriptives

An important feature of the manual BCH 3-Step procedure is the option to include auxiliary variables, specifically covariates and distal outcomes. Recall that a single covariate (school poverty index) was included in the model alongside four distal outcomes related to academic achievement (ELA/English I, Math) and college/career readiness (COCR, CACR). Note that while high school students are measured on ‘English’ not ‘ELA’, the term ‘ENG’ will be used as a catchall term for the remainder of this section to describe academic achievement related to ELA and English I. Descriptive statistics (means and standard deviations) are provided for each auxiliary variable across profiles in Table 4.14. Poverty index appears to be highest in Profile 2 (Elementary school, low climate) and lowest in Profile 5 (High school, high climate). Profile 5 also has the highest rates of students meeting/exceeding ENG and Math standards and being classified as college and/or career ready. The lowest rates for ENG and Math were found in Profile 4 (Middle school, low climate).

Table 4.14 *Descriptive statistics, Mean (SD), of auxiliary variables across profiles*

Profile	Poverty Index	ENG	Math	COCR	CACR
1	61.001	48.553	56.570		
	(20.905)	(15.432)	(15.356)		
2	76.533	33.610	40.188		
	(15.95)	(13.417)	(15.250)		
3	58.791	42.213	41.458		
	(18.908)	(13.909)	(15.539)		
4	68.777	32.849	30.329		
	(18.376)	(13.918)	(15.057)		
5	53.352	57.040	64.084	78.179	42.059
	(19.650)	(16.477)	(16.715)	(12.642)	(20.799)
6	64.586	46.496	63.378	69.809	29.729
	(15.833)	(13.942)	(15.451)	(13.614)	(13.518)

School Poverty Index covariate

Regression of the distal outcomes on the school poverty index covariate was examined to evaluate the relationship between poverty and the distal outcomes across identified profiles. Fairly similar values were found across profiles, especially related to poverty's relationship with ENG and Math. All relationships were negative across classes, illustrating poverty's negative effect on academic achievement and college/career readiness regardless of school climate level. However, the largest difference in regression coefficient values were located between Profile 1 and Profile 6 for ENG (0.158) and Math (0.192), indicating that school poverty had a stronger negative impact on ELA and Math in Profile 6 than in Profile 1. Looking at college/career readiness indicators, poverty seemed to have a more prominent impact on CACR as opposed to COCR. This is

understandable, as COCR is a more flexible measure (students can be either college *or* career ready) than CACR, and it is plausible the schools with higher poverty levels (and the students within them) may have fewer resources to meet both requirements.

Comparing school poverty's impact on CACR and COCR across Profiles 5 and 6, COCR is more heavily impacted in Profile 6 while CACR is more impacted in Profile 5. Considering Profile 5 (High school, high climate) has more positive climate than Profile 6, this suggests that poverty's impact on COCR is higher when school climate is lower but that its impact on CACR is higher when climate is higher, albeit modestly.

Table 4.15 *Relationship between school poverty and distal outcomes*

Profile	ENG on Poverty	Math on Poverty	COCR on Poverty	CACR on Poverty
1	-0.628*	-0.563*	**0.000**	**0.000**
2	-0.699*	-0.733*	**0.000**	**0.000**
3	-0.646*	-0.701*	**0.000**	**0.000**
4	-0.697*	-0.706*	**0.000**	**0.000**
5	-0.720*	-0.642*	-0.434*	-0.879*
6	-0.786*	-0.755*	-0.598*	-0.717*

Note. Bold values are not statistically significant ($p<.05$) because they were fixed at zero to permit model estimation.

*Statistically significant ($p<.05$)

Influence of Poverty Covariate on Latent Profiles. To analyze the influence of the covariate on the identified latent profiles, profiles comparisons were conducted using a referent profile, Profile 1 (Elementary school, high climate), that displayed the highest relative intercept value compared to other profiles (see Table 4.16). Compared to Profile 1, there was a significant effect of poverty on Profile 2 (Elementary school, low climate)

and Profile 4 (Middle school, low climate), and Profile 5 (High school, high climate). However, all regression coefficients were close to zero and odds ratios (comparing each profile to Profile 1) were near one. This means, for example, that for schools in Profile 2, a one unit increase in the poverty index means roughly a 5% greater likelihood of belonging to Profile 2 compared to Profile 1. Thus, it seems as though poverty impacts each profile fairly evenly, though odds ratio values are slightly higher for profiles with lower climate (Profile 2, 4, and 6).

Table 4.16 *Impact of poverty on profile assignment*

Profile	Intercept	Regression coefficient (Class on poverty)	Odds ratio (CI)
2	-3.691*	0.053*	1.055 (1.042 – 1.068)
3	-0.500	-0.005	0.995 (0.985-1.005)
4	-2.478*	0.023*	1.023 (1.010 – 1.036)
5	-0.036	-0.018*	0.982 (0.972-0.993)
6	-1.756*	-0.010	1.011 (1.000-1.021)

Note. Intercept significance values denote a significant difference between a given profile and Profile 1

* Statistically significant ($p<.05$)

Analysis of Distal Outcomes

To analyze distal outcomes for the model, intercept and covariance values were investigated across profiles. Results for each topic are detailed below.

Outcome Intercepts. Looking first to distal outcome intercept values (See Table 4.17), all were found to be statistically significant ($p<.05$) except for those related to COCR and CACR in Profiles 1-4 (elementary and middle schools). For ENG and Math, intercept values were highest for Profile 6 and lowest for Profile 3 and Profile 4,

respectively. Looking at Profiles 5 and 6, values for COCR were higher in Profile 6 and values for CACR were higher for Profile 5.

Table 4.17 *Distal outcome intercepts by profile*

Profile	ENG	Math	COCR	CACR
1	86.943*	90.995*	46.549	-1.120
2	87.029*	96.211*	60.272	17.387
3	80.249*	82.717*	73.994	35.894
4	80.764*	78.813*	73.994	35.894
5	95.505*	98.415*	100.960*	88.352*
6	97.274*	102.073*	108.421*	75.945*

*Statistically significant ($p < 0.05$)

Distal outcomes were then analyzed across profiles to determine if differences were statistically significant (see Table 4.18). For both ENG and Math outcomes, differences between Profiles 1 and 2, Profiles 3 and 4, and Profiles 5 and 6 were statistically insignificant, suggesting that significant differences may not exist across schools with low and high climate when looking *within* school level. Looking beyond statistical significance, differences between these same profiles were much higher for Math than for ENG, with lower-climate profiles having higher levels of achievement in all cases except for middle school Math where schools with more positive climate (Profile 3) had higher Math performance than their low-climate counterparts (Profile 4).

Across all profile comparisons, the largest difference for ENG was between Profile 3 (Middle school, high climate) and Profile 6 (High school, low climate). The smallest statistically significant ENG differences was found between Profile 2 (Elementary school, low climate) and Profile 4 (Middle school, low climate). For

Mathematics, the largest difference was between Profile 4 (Middle school, low climate) and Profile 6 (High school, low climate). The smallest statistically significant difference was between Profile 1 (Elementary school, high climate) and Profile 5 (High school, high climate).

Table 4.18 *Difference in distal outcome intercepts across profiles*

Profile difference	ENG	Math	COCR	CACR
Profile 1- Profile 2	-0.086	-5.216		
Profile 1- Profile 3	6.695*	8.278*		
Profile 1- Profile 4	6.178*	12.18*		
Profile 1- Profile 5	-8.558*	-7.416*		
Profile 1- Profile 6	-10.332*	-11.085*		
Profile 2- Profile 3	6.780*	13.494*		
Profile 2- Profile 4	6.263*	17.396*		
Profile 2- Profile 5	-8.473*	-2.199		
Profile 2- Profile 6	-10.247*	-5.869		
Profile 3- Profile 4	-0.517	3.902		
Profile 3- Profile 5	-15.257*	-15.694*		
Profile 3- Profile 6	-17.027*	-19.363*		
Profile 4- Profile 5	-14.736*	-19.596*		
Profile 4- Profile 6	-16.510*	-23.265*		
Profile 5- Profile 6	-1.774	-3.669	-7.477	12.394*

Note. Negative values indicate that second class is higher than first class measured. Differences for COCR and CACR for profile 1-4 were not applicable and therefore not included.

* Statistically significant ($p<0.05$).

College and/or career readiness outcomes were only compared for Profiles 5 and 6, given that they contained high schools. While Profile 6 (High school, low climate) had

higher COCR intercept values than Profile 5 (High school, high climate), on average, the difference was statistically insignificant. However, differences in CACR intercepts were statistically significant with schools in Profile 5 exhibiting much higher values, on average, than those in Profile 6.

Outcome Covariance. As previously discussed, covariances across distal outcomes were estimated across profiles (with the exception of those including CACR and COCR for Profiles 1-4). Table 4.19 displays the covariance values for each distal outcome combination across profiles. All covariance values are positive, suggesting positive relationships among all combinations of distal outcomes.

Table 4.19 *Profile-specific covariance estimates*

Profile	Math with ENG	COCR with ENG	COCR with Math	CACR with ENG	CACR with Math	COCR with CACR
1	61.448*					
2	53.866*					
3	38.466*					
4	31.447*					
5	72.136*	31.190*	41.815*	62.264*	60.416*	66.226*
6	33.176*	5.762	29.009*	3.269	11.637	27.278*

*Statistically significant (p<.05).

Mplus also allows users to request Tech 7 output which creates sample statistics by weighting raw data with the estimated posterior probabilities for each profile. This is an attempt to create ‘sample statistics’ with mixture models (Muthén, 2013). While this technique is not perfect, it does help with the comparison of distal outcomes across

profiles by providing weighted variances and covariances (see Table 4.20) that allow for the computation of correlations as displayed in Table 4.21.

Table. 4.20 *Weighted variances and covariances from Tech 7 output*

Outcome(s)	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6
Math	231.680	227.510	238.450	221.950	275.790	233.710
ENG	235.240	175.000	191.050	190.230	268.350	189.230
CACR					429.263	174.404
COCR					157.027	182.681
Math-ENG	215.150	180.350	198.860	195.040	249.170	185.840
Math-COCR					207.960	148.209
Math-CACR					290.157	146.170
ENG-COCR					188.074	118.627
ENG-CACR					310.524	138.405
COCR-CACR					200.008	131.159

Table 4.21 *Correlations computed using weighted variances and covariances*

Outcomes	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6	All
Math-ENG	0.922	0.904	0.932	0.949	0.916	0.884	0.917
Math-COCR					0.993	0.710	0.731
Math-CACR					0.838	0.716	0.774
ENG-COCR					0.911	0.630	0.739
ENG-CACR					0.910	0.752	0.852
COCR-CACR					0.770	0.735	0.783

One can see in Figure 4.9 that the correlation between Math and ENG is highest in profiles with higher climate, with the exception of in middle schools where Profile 4 (Middle school, low climate) has a higher correlation value than Profile 3 (Middle school, high climate). In fact, Profile 4 has the highest correlation value between ENG and Math

out of all profiles, while the relationship between these outcomes is the lowest in Profile 6 (High school, low climate). However, correlations between Math and ENG remain high across all profiles, regardless of school level and climate.

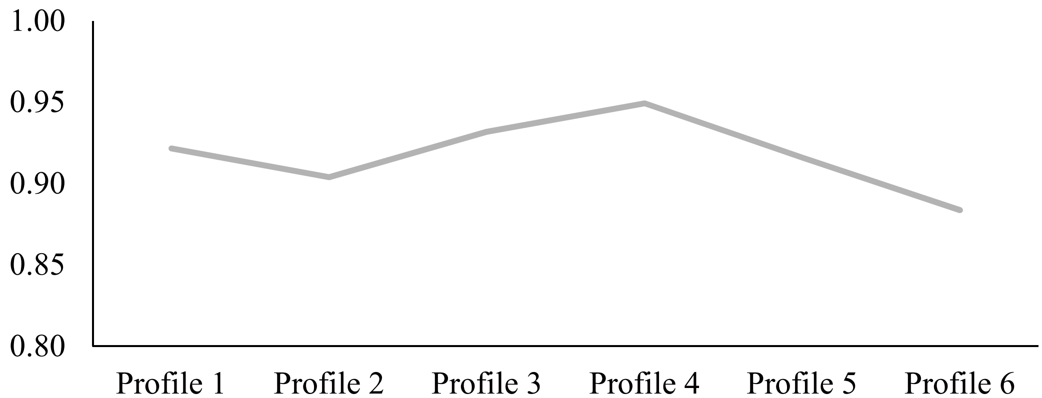

Figure 4.9 *Correlation between Math and ENG across profiles*

The relationships between COCR and CACR for both Math and English were stronger in Profile 5 (High school, high climate) than in Profile 6 (High school, low climate), as displayed in Figure 4.10. Though, differences in correlation values between profiles were larger for COCR than CACR. This suggests that academic indicators *could* be more predictive of college/career readiness (especially COCR) in schools with better climate.

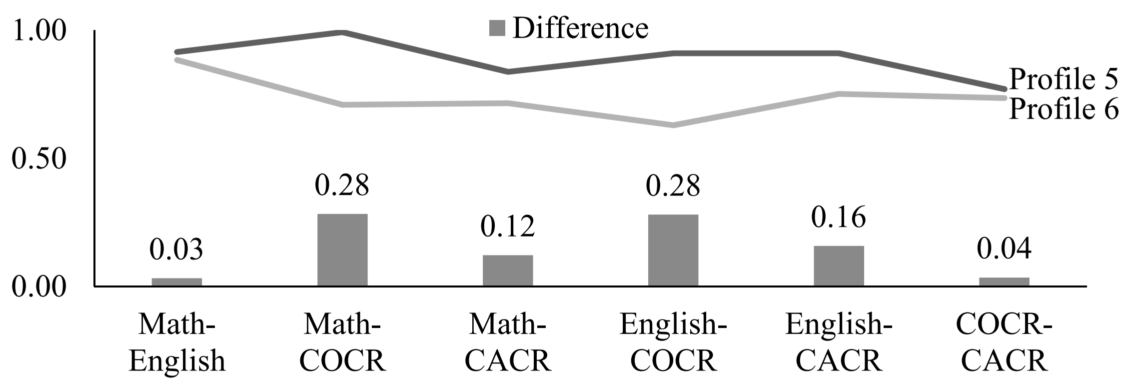

Figure 4.10 *Correlations computed using weighted variances and covariances*

Summary

The findings shared in this chapter help provide insight regarding research question 1 pertaining to the types of profiles identified when examining school climate at the student- and school-levels and in relation to school poverty, academic achievement, and college/career readiness.

Profiles for students were classified both by level of school climate and where those levels occurred (i.e., which items or factor were respectively high/low). As a result, students were able to be classified into six profiles that extended beyond the typical "high" vs. "low" climate continuum. For example, for the two profiles found to have "below average" climate, Profile 2 highlighted students' concerns regarding learning environment while Profile 3 highlighted students' concerns for social-physical environment and safety.

At the school level, the typical climate continuum (high and low) was expanded by addling a dimension of school type (elementary, middle, and high) as well as analyzing profiles in relation to school poverty, academic achievement, and college/career readiness. Regarding school poverty, its impact on class assignment appeared fairly even across profiles, though odds ratios were slightly higher for Profiles 2 and 4 (elementary, low climate and middle school, low climate) compared to Profile 1, suggesting that increases in poverty could result in slightly higher odds of being a school with low climate.

Looking within school level, differences between profiles tended to be greater in Math than in English. Middle school profiles (Profiles 3 and 4) were the only set where the profile with higher climate (Profile 3) displayed higher achievement compared to the

profile with lower climate (Profile 4). However, all differences between ENG and Math were statistically significant when looking across profiles within school level.

For college/career readiness, Profile 5 (High school, positive climate) had higher CACR than Profile 6, and this difference was statistically significant. Profile 6 had higher COCR than Profile 5, but this difference was smaller in size and was not statistically significant. These patterns suggest that CACR will be higher in high schools with positive climate, and points to the possibility that COCR rates may be higher in schools with comparatively low climate.

While this chapter was able to provide information regarding the first research question, the remaining two questions are better suited to be discussed in Chapter 5. There, they will be examined the context of the study's findings as well as its limitations, relevance, and usefulness in terms of its methodology and potential to impact policy as it relates to school climate.

CHAPTER 5

DISCUSSION

The previous chapters have presented the purpose, methods, and results of the current study in an attempt to shed light on a series of research questions. The first research question was centered on the identification of latent profiles at the student and school levels. The second and third research questions were focused on whether the methods employed to identify these profiles were effective in analyzing school climate from the standpoints of methodology and policy. This chapter includes in-depth discussions aligned to the each research question, their relative findings, and potential impact. Limitations of the current study then presented along with suggestions for further research and a final conclusion.

Identifying Profiles and Auxiliary Relationships

The first research question of this study involved the identification of climate profiles at both the student and school levels. It also sought to better understand the relationship between these profiles and a set of auxiliary variables, specifically school poverty level as a covariate and distal outcomes involving academic achievement and college/career readiness. The following subsections discuss important considerations in the profile enumeration process as well as the importance of specific findings from the analyses and important questions to consider moving forward.

Considerations in profile enumeration

One of the most important considerations in this process was the selection of the 'appropriate' number of profiles. This was especially difficult at the student level given the inherent variation of responses among such a large sample. This variation left more room for various patterns of item values to appear within and across factors than at the school level where responses were averaged by school.

The determination of which variations were important or practically significant from one model solution to the next was highly subjective and greatly depended on the outlook of the researcher. At the student level, the reasoning for selecting six profiles was highly influenced by the goal to identify different *types of students* (or student perceptions) as opposed to identify different types of climate. Each of the six profiles represents a type of student and their outlook on their school and its climate. For example, some students perceived their school climate as being extremely low and expressed concerns for their safety. Other students may have had low perceptions of climate but identified different areas that they felt needed more focus such as the social-physical environment or home-school relationships.

From this perspective, a goal of the current analysis (at the student level) was to investigate *where* students differed in their perceptions of climate. Looking at climate this way raises several important questions for future analyses. For example, are certain types of students more or less prevalent in certain schools or types of schools or are they evenly represented? What do students who have different climate profiles have in common and how do they differ by student characteristics such as race/ethnicity, gender, rate of absenteeism, mobility status, English language proficiency, grade point average, and

parental involvement? While we can currently identify who these students are in terms of their perceptions of school climate, more work needs to be done to identify important characteristics that could further illuminate *why* they experience climate differently from their peers.

While these considerations were important in arriving at the appropriate number of profiles at the student level, profiles at the school-level could be conceptualized as being on a clear low-high continuum. Profiles at the student level displayed a continuum to a certain degree. However, what differentiated student profiles the most was *where* students were high or low on certain items or factors. This prompts ones to ask which approach more appropriate – categories or continuums?

Past work analyzing South Carolina school climate has identified it as being on a continuum (DiStefano et al., 2016) and others have followed suit from identifying students as having negative, moderate, or positive climate (Van Eck, 2017). Looking specifically at behavior and social-emotional skills, others identified students as being either at high-risk, at-risk, normative (average), or socially-emotionally skilled, creating another continuum-like scale (Bradshaw et al., 2015).

However, other work involving school climate has focused more on identifying profiles based on where students or schools are high or low on respective factors. For example, Lorenzo-Blanco (2016) identified profiles based on the relative position of factors based on discrimination, victimization, school safety, and social support. Mayworm (2016) also identified school climate profiles in a similar fashion, assigning students profiles of uninvolved, authoritarian, permissive, or authoritative based on combinations of item responses. Allison et al. (2016) utilized a similar approach using a

student drug use and health survey and identified four profiles of unhealthy, distressed, substance-using, and healthy students. Both Allison et al. (2016) and Mayworm (2016) also created upper-level profiles based on the presence of lower-level profiles (non-parametric multilevel latent class analysis).

Looking beyond how climate is presented in the research, school climate can also be conceptualized and presented differently on state report cards. For example, Illinois displays each component of the school climate survey and assigns various color schema based on the level of implementation at each school. While each survey component is assigned a level of implementation that is on a continuum (least to most implementation), schools can also be compared based on which components are low or high relative to each other. This illustrates that while overall climate can be conceptualized as being on a continuum, this continuum may not hold across each subcomponent of the construct, and it is up to us to determine whether that is an important finding to share.

Further, a researchers' ability to pinpoint potential differences in the construct across profiles may heavily depend on the number of profiles selected. Thus, another consideration in the category-continuum debate is the number of identified categories or levels and whether they are more informative than they are complicated or confusing.

Methodologically, it was more complicated to analyze and compare models with more profiles compared to those with fewer profiles. At the student level, the complexity was outweighed by the value of identifying student profiles that could better point to their needs and values that may otherwise be overlooked. However, at the school level, the information with two profiles was just as useful as it was with four profiles and item patterns did not diverge from a clear continuum.

It would seem then that one's decisions regarding continuums, categories, and profile enumeration, while guided by previous findings, is heavily context-dependent. The current study supports the existence of climate on a continuum but acknowledges that at some point this continuum deviates across climate items and factors and that these deviations are an important avenue to explore in the context of latent profile analysis if one's goal is to pinpoint specific areas of growth and concern.

Significance of findings

Apart from the number of profiles selected in both the student- and school-level analyses, some important findings were uncovered in the current study. Because the BCH 3-Step approach was not applied at the student level, there are no other relevant findings at this level apart from those concerning profile enumeration as discussed in the previous section. Thus, this section will focus on the findings gathered from the school-level analysis.

School Poverty. Looking first to the school poverty index, within each school level (elementary, middle, high), poverty appeared to be higher in profiles with low climate. Poverty also had a stronger negative relationship with ENG and Math in profiles with low climate. While this relationship was fairly consistent across school levels, it tended to be strongest at the high-school level and weakest in elementary. This suggests that poverty level may not be as predictive of performance in elementary as it is in middle and high school and that persistent exposure to poverty at the school- or student-level could impact student achievement over time, especially in schools with lower climate.

Regarding college/career readiness, school poverty had a stronger negative relationship with COCR in low-climate schools compared to high-climate schools.

However, for CACR, poverty's impact was more severe in schools with high climate. The data shows that schools with higher climate also have a higher proportion of students identified as being CACR (42% compared to 30% for low-climate schools). Therefore, it is possible that the relationship is more severe because a larger number of students would be impacted. Also, because the poverty index also tends to be lower in schools with positive climate, this finding also suggests that schools with lower climate (and higher poverty) may have less access to quality programming that would make CACR designations more prevalent.

Together, these findings point to the pervasive impact of poverty on student achievement and potentially school climate. Poverty impacts student life within and outside of the classroom, from nutrition to transportation, parental involvement, and access or exposure to extracurricular educational opportunities. It can further affect the quality of teachers, learning materials, and access to courses. In essence, poverty negatively impacts students' opportunity to learn while remaining largely unmalleable by schools or districts. Future studies should incorporate covariates that are more responsive to interventions, perhaps using the Opportunity to Learn (OTL) standards adopted throughout the country as a guide.

A final interesting finding related to school poverty was its impact on profile designation when compared to the referent profile with the most positive climate (Profile 1: Elementary school, high climate). A one-unit increase in the poverty index was purported to increase the likelihood of an elementary school belonging to a low-climate profile compared to a high-climate profile by 5.5%. It also would increase the odds of a school belonging to Profile 4 (middle school, low climate) compared to an elementary

school with high climate by 2.3%. However, for high schools, a one unit increase in the poverty index would decrease the odds of a school belonging to Profile 5 (high school, high poverty) compared to the referent profile by 1.8%. While these odds ratios seem low, the poverty index ranges from zero to 100 points. Thus, an increase of five points on could have a compound effect on the odds ratios outlined above.

These comparisons also bring up an important question when using referent profile comparisons across known classes. Traditionally, each class is compared to a single referent class (in this case, Profile 1). In the current analysis, one could argue for the use of separate referent classes for each school level which would allow for analysis of odds ratios within each level. To the knowledge of the researcher, this practical approach is not commonplace and was therefore not used in the current study. Though, this issue does point to a need for a future investigation of this method of model interpretation.

Distal Outcomes. The distal outcomes focused on levels of student achievement and college/career readiness within schools. Achievement in English and math tended to be higher, on average, in schools with higher climate. Interestingly, while CACR and COCR rates were also higher in schools with higher climate, the gaps between low- and high-climate schools were smaller for COCR. Again, this suggests the possible need for increased access or supports for students in schools with low climate and higher poverty levels.

Distal outcomes were compared using intercept values that represent the degree to which the latent class impacts each outcome. Within school levels, the differences in ENG intercepts between low- and high-climate profiles were fairly small and statistically

insignificant. For math, within-level intercept differences between low- and high-climate schools were also statistically insignificant. This suggests that whether a school is defined as having low or high climate may not have a significant impact on a school's overall ENG or math performance.

While intercept differences between low- and high-climate profiles were not largely present *within* school levels for academic outcomes, outcomes related to college/career readiness painted a slightly different picture. At the high school level, intercept differences between low- and high-climate profiles were not statistically different when looking at COCR, though the low-climate profile had slightly higher intercept values than the high-climate profile. The opposite pattern was found for CACR, where a significantly higher CACR intercept value was found in the high-climate profile. These findings suggest that high schools with low climate may have a larger impact on COCR rates compared to those with high climate (pending a statistically significant result is found). But high schools with high climate have a significantly larger impact on CACR rates compared to those with low climate. This again points to the important difference between COCR and CACR and its relevance to preparing our graduates to excel in their postsecondary endeavors. While it is expected that higher rates of COCR will exist compared to CACR, these differences should not also be tied to school differences in climate or poverty level. When they are, this suggests that COCR is not only a broader measure of postsecondary readiness but a measure of inequity when viewed in tandem with CACR rates within and across schools.

Finally, the correlations among outcomes revealed that math and English achievement was more highly correlated in schools with high climate compared to those

with low climate except for middle schools. Middle schools also exhibited the highest correlational values across all levels. These patterns imply that academic success in one subject may be slightly more predictive of academic success in another subject in schools with higher climate. It is possible that in schools with lower climate, other factors may reduce the strength of this relationship. The anomalous patterns in middle schools, however, suggest that the content of the assessments may be more aligned in terms of difficulty. They may also be a reflection of the various academic and personal transitions students undergo during that period. Thus, students may have more negative affect in general that is captured by the school climate survey, making it a more nebulous measure of school climate, and allowing for deviations from what is expected (i.e., higher correlation between achievement measures in low-climate schools).

For high schools, the correlational values related to CACR and COCR were higher for high-climate compared to low-climate profiles. The highest correlational value was between math and COCR. This value in addition to the one between English and COCR also exhibited the largest gaps between profiles, while the correlation between COCR and CACR were very similar across profiles. Differences in correlational values between profiles were also larger for COCR than CACR. Together, these patterns suggest that academic indicators could be more predictive of college/career readiness (especially COCR) in schools with better climate.

Important Concepts Moving Forward

The previous discussion of the results highlights the need for a greater focus on poverty and equitable access to programming, resources, and supports when looking at school climate. It also emphasizes the need for a more in-depth student-level analysis.

The application of the manual BCH 3-Step at the student-level could have produced a more detailed look at the types of student profiles which could have made their utility more readily apparent. Finally, the discussion of profile enumeration illuminates the complexities involved in arriving at a model that is informative but not overly complex. This final concept is something that will be explored more in the next section as it relates to the second research question in the study.

Usefulness of Items Compared to Aggregated Scores

The second research question of this study focused on whether creating profiles based on item-level data is an effective strategy compared to using aggregated scores in terms of application and interpretability. This section attempts to answer this question from both methodological and policy perspectives.

Methodological Perspective

From a methodological viewpoint, the decision to use item-level or aggregate scores is likely based on either the impact on the model estimation process and/or the desired level of variability/detail one wishes to capture. While the current study used item-level responses, previous studies of South Carolina school climate used factor scores. For example, in the study by DiStefano et al. (2016), each observation had four factor scores—one for each factor on the survey (i.e., home-school relationship, safety, social-physical environment, and learning environment).

The reasoning behind using factor scores lies in their simplicity. They represent each student's overall perspective on a given factor and can be easily compared to each other and across profiles. The aggregate nature of factor scores also aids in the model

estimation process, as fewer parameters exist and can be easily freed with less likelihood of encountering convergence errors.

However, the ease of model estimation comes at the expense of detail and item variability in the model. The inclusion of item-level data may have enabled additional or different types of profiles to be identified. Further, a more granular view of each profile was possible. This permitted the explorative comparison of item-level results within factors and across profiles to determine exactly *how* different profiles were at the item level in addition to the factor level. But the use of item-level data also presented some problems. Specifically, it increased the number of model parameters to such a large extent that it inhibited the model estimation process when all parameters were allowed to be freely estimated in the student-level model.

It is difficult to definitively state whether an item- or factor-level analysis was more appropriate in the current study. At both the school and the student levels, items seemed to have fairly similar values within each factor –though some were more varied than others at the student level. This suggests that perhaps a factor-level analysis may allow for similar conclusions with less computational complexity. Thus, while an item-level analysis proved educational and provided detailed information, from a methodological standpoint, it is likely to yield similar results.

However, this conclusion would have to assume that the same profiles would have been discovered using the factor-level analysis, which is unlikely given previous findings (e.g., DiStefano et al., 2016). Future studies could investigate differences in using item- and factor-level data in mixture modeling in greater detail. The placement of

items within factors and within and across profiles could also be analyzed to identify patterns and determine whether they reflect certain item characteristics or content.

Policy Perspective

The same concerns regarding the balancing of model information and simplicity that were discussed in the methodological section persist when considering the effectiveness of using item- or factor-level data from a policy perspective. In fact, one could argue that the argument for simplicity is even more pertinent when presenting ideas and findings to policymakers. This is because policymakers' livelihoods rely on conveying ideas and arguments to the general public. Furthermore, the sheer amount of information policymakers receive on a daily basis from their constituents, fellow policymakers, government officials, researchers, content experts, and school leadership and staff necessitates that any information shared with them be concise, easy to understand, and appealing to the general population.

With all of this in mind, one could generally say that factor-level responses are more appropriate. Not only do factors provide a general, birds-eye view of how students and schools perceive school climate, but they may also yield profiles that are similarly general and portray climate as an easy-to-understand continuum (as has historically been done when using latent profile analysis and factor-centered methodologies).

However, one could also argue that the actions performed by researchers in coordination with schools could uncover findings using item-level responses that would eventually inform policy. This perspective is both admirable and a bit naïve. It also forces us to ask ourselves at what point do we change our methodology in a bid to influence

policy, what (if any) information is lost, and is that potential loss of information acceptable if it allows us to have a potentially positive impact in the education sector?

For the current study, while an item-based analysis yielded interesting student-level profiles, there is no question that using fewer profiles would allow for clearer communication of school climate findings. This is especially true when one add additional elements such as covariates or distal outcomes that can add to the complexity of a presentation of school climate information. Thus, from a policy perspective, the argument for factor-based scores is likely a stronger one, though item-based scores can still prove to be a useful tool for supplementary analyses that indirectly inform policy through further research.

Effectiveness of Mixture Modeling and the BCH 3-Step Approach

The current study sought to apply mixture modeling and the BCH 3-Step approach because they allow for person-centered analyses with the incorporation of auxiliary variables. Methodological and policy considerations as they relate to the current and future study of school climate are discussed below.

Methodological perspective.

The application of mixture modeling in this study contributed to the scant literature on person-centered evaluations of school climate. However, it was made evident that significant advancements in the literature are needed to make the BCH 3-Step approach more approachable and easily applied for multilevel models.

While resources existed separately for the manual approach for single-level models and for non-parametric models, the coding schema for blending a multilevel latent profile analysis (LPA) with a non-parametric model were limited and code for a

multilevel model using the BCH 3-Step were seemingly non-existent. Given that a few studies had suggested the application of a multilevel mixtures using the BCH 3-Step, it was assumed that a work-around could be utilized to arrive at a properly-working model using the chosen statistical software. In effect, a trial-and-error approach was adopted wherein multiple coding options were applied and none succeeded to arrive at the intended result.

Having reached the limit of creative coding variations and asking for input from subject matter experts, it was decided that single-level models would be analyzed for the current study. The issues faced in the current study point to the increased need for researchers to make their code more widely available, especially when it involves new concepts. However, this is made more difficult considering that the statistical software currently has no guidance on how to conduct a multilevel LPA using the manual BCH 3-Step approach. It would be useful if future iterations of the Mplus software allowed for the analysis of these types of models.

The value of a multilevel application would be especially useful in mixture models as it relates to education where most data is nested in nature. In the current study, it would have allowed for a more complex and in-depth analysis that has yet to be done using the South Carolina school climate survey. It would have also proven very informative if only performed at the student-level using student-level distal outcomes and covariates. Future studies could easily employ the second option if student-level data for possible auxiliary variables (e.g., race/ethnicity, family income, absenteeism rate) are readily available.

In sum, the relative newness of the manual BCH 3-Step was both a methodological boon and burden. Investigating a new method and its incorporation in the available statistical software was a rich learning experience. And while it was not possible to conduct the approach using the proposed multilevel or student-level models, the use of the BCH 3-Step for the school-level analysis using the KNOWNCLASS option for school level yielded a new view of school climate that has not yet been analyzed for school climate in South Carolina. The BCH 3-Step, and mixture models in general, should continue to be used to examine school climate and foster the growth of student-centered analyses in the area. However, these methods would be most useful using a multilevel approach that can also accommodate covariates and distal outcomes. Thus, while the multilevel BCH 3-Step is ideally preferred for deeper analyses of school- and student-level data, its application for separate levels is effective and informative enough to support its continued use in education.

Policy Perspective.

From a policy perspective, there are two main benefits of using the BCH 3-Step approach and mixture modeling to inform decisions about school climate. The first is the focus on student- and/or school-centered analyses. Oftentimes in policy, and especially as it relates to accountability in education, the focus is on the numbers and academic achievement. Increased attention on student-centered analytic procedures such a mixture modeling could provide a much-needed counterweight by helping to identify certain types of students (using school climate or other surveys/instruments), especially those most in need of certain supports.

This leads to the second benefit of the BCH 3-Step approach which is the ability of looking at climate in relation to important covariates and distal outcomes. School climate is measured because it is believed to have some impact on students' academic achievement—whether directly or indirectly. However, the opportunities to evaluate school climate with other important outcomes are limitless. Future studies could extend to include non-academic outcomes such as suspensions, dropouts, measures of social-emotional learning. Additional covariates could also be examined such as teacher quality or 'impact', geographic location or characteristics, and the availability of advanced coursework. If certain profiles of student and schools can be identified using mixture modeling, then their commonalities and differences as they relate to auxiliary variables could point to fundamental needs that may or may not being addressed on a large scale by policymakers. For example, the difference in college *and* career readiness across low- and high-climate schools suggests that an investigation of the quality and access of advanced programming is likely needed.

In using the BCH 3-Step and mixture modeling, we can also analyze whether certain student characteristics are more/less predictive of school climate responses than the schools they attend. For example, the anomalous patterns in middle school profiles suggested that the life experiences of those students may be fundamentally different than in elementary school and high school to the extent that it impacts their responses to the climate survey differently than in the other two groups. Future studies could look for similar findings based on other student characteristics.

A potential downfall of using the BCH 3-Step approach from a policy perspective is that it has the capacity to become quite complex if model selection and data format are

not carefully considered (as discussed in the previous section regarding item- and factor-level data). There is also the concern of whether student-centered analyses are considered valuable by those in the policy arena. Most decisions in education are made in an effort to increase academic achievement. Shifting focus onto types of schools and/or student profiles based on climate, while interesting, is not likely to gain traction unless it is easy to conduct and understand, is clearly connected to student outcomes, and is better than (or substantially adds to) what is already being done.

If the conclusions garnered from mixture modeling are the same as those from item-centered analyses, then the argument for using the former in addition to or in lieu of the latter is substantially reduced. Further, given the importance of simplicity in presenting findings to policy makers and its potential impact on the profile enumeration process, it is also possible that the added benefits of employing a person-centered approach may be slightly curbed. However, future studies can examine both of these concerns by comparing the perceived usefulness and outcomes of item- and person-centered approaches. Researchers could also examine if and how student- and school-level policy decisions would vary across approaches and if assigning students- and schools- to profiles aides in the presentation of item-centered analysis results to schools or districts.

Scholarly Significance and Limitations of Current Study

The current study is significant in that is contributes to the sparse array of literature at the cross-section of mixture modeling and school climate. To date, the South Carolina school climate survey has not been analyzed at the school-level using the BCH 3-step approach with the selected array of distal outcomes. Further, while previous work

presented climate on more of a continuum at the student-level, the current study adopted a categorical presentation of the construct, focusing on where items/factors presented high or low and how these differed within and across profiles. This study also employed item-level instead of factor-level data that may have yielded different profiles than if a factor-level dataset been used.

While this study presented data in new and interesting ways using a relatively new method, there were several limitations that need to be addressed. The first, and most obvious, limitation is that a multilevel LPA (MLPA) was unable to be analyzed using the BCH 3-Step approach. Given that the school climate data is nested (students within schools), analyzing the data within a multilevel model would have been optimal. It would have also allowed for student level data to be analyzed in coordination with the selected covariate and distal outcomes. If and when the modeling software allows for the implementation of an MLPA using the BCH 3-Step, this study should be carried out as initially intended and the conclusions from each study should be compared.

A second limitation of the current study was the complexity of the model that resulted from the use of item-level data. This precluded the ability to free all of the model parameters and relax the assumptions of the model. Perhaps future studies should attempt to determine if any significant differences in profile assignments or relationships involving covariates and distal outcomes arise if these can be successfully relaxed in a school- and/or student-level analyses or in a multilevel analysis if estimation capabilities change or improve in the chosen modeling software.

The complexity of the student-level model also impacted the decision to look at a maximum of six profiles. This decision was guided by the decreasing profile sizes

increasing complexity involved in interpreting the student-level profiles. However, in retrospect, it would have been prudent to evaluate models with more profiles than the selected model to look for possible improvements or glean additional information.

A final limitation of the study was that while item-level data was collected, profiles were analyzed mostly at the factor level. While using item-level data was valuable in that it provided the opportunity to look for item-level variations within factors, those that were identified didn't significantly impact the interpretation of results. However, it may be valuable for other studies to consider item-level models if there is an interest in identifying different distributions of items across profiles.

Despite these limitations, the current study was successful in shedding light on the utility of employing mixture modeling and the BCH 3-Step approach to the analysis of school climate. Suggestions for how these methods and findings can contribute to further research are discussed in the following section.

Additional Suggestions for Future Research

Even though several recommendations for future research have been outlined in the preceding sections of this chapter, there are several ideas that have yet to be discussed that are not directly aligned to each research question. For example, the current study used a version of the survey that did not include items related to bullying. Future studies could examine if and how the inclusion of these items impacts both profile enumeration and the relationships between profiles and auxiliary variables, especially as it relates to poverty and school level.

Similar analyses could also be extended to teacher surveys with the inclusion of teacher-level covariates and outcomes (e.g., years of teaching experience, attrition, or

mobility). While an analysis of parent surveys would be interesting, the response rates are often too low to be useful. However, it is possible that this information could be analyzed to determine whether parent response rates vary substantially across profiles. The study could also be expanded to include variables that are more actionable such as student-teacher or -counselor ratios, after-school programming and tutoring, teacher professional development, use of restorative practices, and availability of advanced coursework.

Next, the current study used a very large sample including students across the state of South Carolina. This may not always be possible or preferred. An alternative could be to create and compare models using smaller random samples from the population of interest. Smaller samples could also be taken within each district, by geographic area (e.g., rural, suburban, urban), or even within a school of interest. However, more complex models may perform better with larger datasets, as there is more information available, and the number of identified profiles could also vary by the size of the sample (see Marsh et al., 2009).

Finally, it is possible that South Carolina will adopt another survey to meet ESSA accountability standards that is different from the one analyzed in the current study. If this occurs, it would be interesting to identify and compare student- and/or school-profiles using data from both instruments. The relationships between profiles and auxiliary variables could also be compared. Even if one wanted to retroactively compare the results of the SC school climate survey to the previously-used Cognia survey, this would also prove useful given that the latter is currently used by several states to meet accountability requirements.

Conclusion

As the evolution and innovative applications of mixture modeling continue, it is likely that new and exciting information with regards to school climate, and education as a whole, will emerge. The central aim of this study was to view school climate in South Carolina through a new lens that was both person-centered and guided by methodological and policy concerns. This goal was initially meant to be accomplished via a multilevel application of the manual BCH 3-Step approach. However, the alternative models and examination of the methodological choices within them not only magnified important relationships between school climate, school poverty, and student outcomes but illuminated the way for future research, policy, and practice.

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APPENDIX A

SC SCHOOL CLIMATE SURVEY ITEMS AND DOMAINS (2018)

Table A.1 *SC school climate survey items and domains (2018)*

Survey Domain and Item Number	Survey Item Text
LE1	My classes are challenging (not too easy; they make me think).
LE2	My teachers want me to understand what I am learning, not just remember facts.
LE3	My teachers expect students to learn.
LE4	My teachers expect students to behave.
LE5	My teachers spend enough time helping me learn.
LE6	My teachers help students when they do not understand something.
LE7	My teachers do a good job teaching me mathematics.
LE8	My teachers do a good job teaching me English language arts.
LE9	My teachers give tests on what I learn in class.
LE10	My teachers give homework assignments that help me learn better.
LE11	My classes are interesting and fun.
LE12	Students at my school believe they can do good work.
LE13	My teachers praise students when they do good work.
LE14	Work done by students can be seen on the walls of my school.
LE15	The textbooks and workbooks I use at my school really help me to learn.

Survey Domain and Item Number	Survey Item Text
LE17	I use computers and other technology at my school to help me learn.
LE18	I am satisfied with the learning environment in my school.
SP1	The grounds around my school are kept clean.
SP2	The hallways at my school are kept clean.
SP3	The bathrooms at my school are kept clean.
SP4	Broken things at my school get fixed.
SP5	There is enough room for students to learn at my school.
SP6	Students at my school behave well in class.
SP7	Students at my school behave well in the hallways, in the lunchroom, and on school grounds
SP8	Students at my school know the rules and what happens when students break the rules
SP9	The rules about how students should behave in my school are fair.
SP10	The rules for behavior are enforced at my school.
SP11	I feel safe at my school before and after school hours.
SP12	I feel safe at my school during the school day.
SP13	I feel safe going to or coming from my school.
SP14	Students from different backgrounds get along well at my school.
SP15	Teachers and students get along well with each other at my school.
SP16	Teachers work together to help students at my school.
SP17	I have seen or know of another student being bullied.
SP18	I have been bullied at school during the school day.
SP19	I have been bullied while going to or from school.
SP20	I have been bullied by someone from my school using a computer, the internet, a cell phone or other electronic device.
SP21	Adults at my school prevent bullying from happening.
SP22	I can always go to adults at my school if I am being bullied.

Survey Domain and Item Number	Survey Item Text
SP23	An adult at my school has talked to me about bullying.
SP24	I have bullied another student at my school.
SP25	I am satisfied with the social and physical environment at my school.
HS1	My parent knows what I am expected to learn at school.
HS2	My parent knows how well I am doing in school.
HS3	My school informs parents about school programs and activities.
HS4	Parents at my school know their children's homework assignments.
HS5	My parent helps me with my homework when I need it.
HS6	Parents are welcomed at my school.
HS7	Parents volunteer and participate in activities at my school.
HS8	I am satisfied with home-school relations.

Note. Domain names are LE="Learning Environment", SP="Social-Physical Environment", HS="Home-School Relations."

APPENDIX B

LIST OF DATABASES

Academic Search Complete, Agricola, AHFS Consumer Medication Information, Alt HealthWatch, America: History & Life, American Antiquarian Society (AAS) Historical Periodicals Collection: Series 1, American Antiquarian Society (AAS) Historical Periodicals Collection: Series 2, American Antiquarian Society (AAS) Historical Periodicals Collection: Series 3, American Antiquarian Society (AAS) Historical Periodicals Collection: Series 4, American Antiquarian Society (AAS) Historical Periodicals Collection: Series 5, Anthropological Index Online, Applied Science & Technology Source, Art Full Text (H.W. Wilson), Art Index Retrospective (H.W. Wilson), Associates Programs Source, Atla Religion Database with AtlaSerials, Biography Index Past and Present (H.W. Wilson), Biography Index Retrospective: 1946-1983 (H.W. Wilson), Biography Reference Bank (H.W. Wilson), Biological & Agricultural Index Plus (H.W. Wilson), Book Review Digest Plus (H.W. Wilson), Book Review Digest Retrospective: 1903-1982 (H.W. Wilson), Business Abstracts with Full Text (H.W. Wilson), Business Source Complete, Children's Core Collection (H.W. Wilson), CINAHL Complete, CINAHL Plus with Full Text, Communication & Mass Media Complete, Computer Source, Criminal Justice Abstracts with Full Text, Current Biography Illustrated (H.W. Wilson), eBook Academic Collection (EBSCOhost), eBook Collection (EBSCOhost), EconLit, Education Full Text (H.W. Wilson), Education Index Retrospective: 1929-1983 (H.W. Wilson), Education Source, Entrepreneurial Studies

Source, ERIC, Essay and General Literature Index (H.W. Wilson), Essay and General Literature Retrospective (H.W. Wilson), European Views of the Americas: 1493 to 1750, Fiction Core Collection (H.W. Wilson), Film & Television Literature Index with Full Text, Fuente Académica, Funk & Wagnalls New World Encyclopedia, General Science Full Text (H.W. Wilson), Graphic Novels Core Collection (H.W. Wilson), GreenFILE, Health and Psychosocial Instruments, Health Source - Consumer Edition, Health Source: Nursing/Academic Edition, Historical Abstracts, History Reference Center, Hospitality & Tourism Complete, Humanities Source, Index to Legal Periodicals & Books Full Text (H.W. Wilson), Index to Legal Periodicals Retrospective: 1908-1981 (H.W. Wilson), International Bibliography of Theatre & Dance with Full Text, International Security & Counter Terrorism Reference Center, Jewish Studies Source, Library Literature & Information Science Full Text (H.W. Wilson), Library Literature & Information Science Retrospective: 1905-1983 (H.W. Wilson), Library, Information Science & Technology Abstracts with Full Text, Life Magazine Archive, Literary Reference Center, MAS Ultra - School Edition, MasterFILE Premier, MathSciNet via EBSCOhost, MEDLINE with Full Text, Mental Measurements Yearbook with Tests in Print, Middle and Junior High Core Collection (H.W. Wilson), Middle Search Plus, Military & Government Collection, MLA Directory of Periodicals, MLA International Bibliography, Newspaper Source Plus, Newswires, Nonfiction Core Collection (H.W. Wilson), Play Index (H.W. Wilson), Political Science Complete, Primary Search, Professional Development Collection, PsycARTICLES, Psychology and Behavioral Sciences Collection, PsycINFO, PsycTESTS, Readers' Guide Full Text Mega (H.W. Wilson), Readers' Guide Retrospective: 1890-1982 (H.W. Wilson), Regional Business News, Religion and

Philosophy Collection, RILM Abstracts of Music Literature (1967 to present), RIPM - Retrospective Index to Music Periodicals, Science Reference Center, Senior High Core Collection (H.W. Wilson), Short Story Index (H.W. Wilson), Short Story Index Retrospective: 1915-1983 (H.W. Wilson), Small Business Reference Center, Social Sciences Full Text (H.W. Wilson), Social Work Abstracts, SPORTDiscus with Full Text, Teacher Reference Center, TOPICsearch, Vocational and Career Collection, Web News, Women's Studies International, MasterFILE Reference eBook Collection, Literary Reference eBook Collection

APPENDIX C

STUDENT CLIMATE SURVEY STRUCTURE

Table C.1 *Student climate sections and items*

Survey Section	Items
Learning Environment	My teachers help students when they do not understand something.
	My teachers spend enough time helping me learn.
	My teachers want me to understand what I am learning, not just remember facts.
	My teachers do a good job teaching me mathematics.
	My teachers expect students to learn.
	My classes are interesting and fun.
	My teachers give tests on what I learn in class.
	Teachers work together to help students at my school.
	My teachers praise students when they do good work.
	My teachers give homework assignments that help me learn better.
	The textbooks and workbooks I use at my school really help me to learn.
	I am satisfied with the learning environment in my school.
	My teachers do a good job teaching me English language arts.
	My teachers expect students to behave.
	The rules about how students should behave in my school are fair.
	I use computers and other technology at my school to help me learn.
	Work done by students can be seen on the walls of my school.
	The media center at my school has a good selection of books.
	My classes are challenging (not too easy; they make me think).

Survey Section	Items
Learning Environment	My teachers help students when they do not understand something.
	My teachers spend enough time helping me learn.
	My teachers want me to understand what I am learning, not just remember facts.
	My teachers do a good job teaching me mathematics.
	My teachers expect students to learn.
	My classes are interesting and fun.
	My teachers give tests on what I learn in class.
	Teachers work together to help students at my school.
	My teachers praise students when they do good work.
	My teachers give homework assignments that help me learn better.
	The textbooks and workbooks I use at my school really help me to learn.
	I am satisfied with the learning environment in my school.
	My teachers do a good job teaching me English language arts.
	My teachers expect students to behave.
	The rules about how students should behave in my school are fair.
	I use computers and other technology at my school to help me learn.
	Work done by students can be seen on the walls of my school.
	The media center at my school has a good selection of books.
	My classes are challenging (not too easy; they make me think).
Home-School Relationship	My parent knows what I am expected to learn in school.
	My parent knows how well I am doing in school.
	My parent helps me with my homework when I need it.
	Parents at my school know their children's homework assignments.
	My school informs parents about school programs and activities.
	Parents are welcomed at my school.
	Parents volunteer and participate in activities at my school.
	I am satisfied with home-school relations.

Survey Section	Items
Social-Physical Environment	Students at my school behave well in the hallways, in the lunchroom, and on school grounds.
	Students at my school behave well in class.
	The bathrooms at my school are kept clean.
	The grounds around my school are kept clean.
	The hallways at my school are kept clean.
	Students from different backgrounds get along well at my school.
	Teachers and students get along well with each other at my school.
	Broken things at my school get fixed.
	Students at my school believe they can do good work.
	I am satisfied with the social and physical environment at my school.
Bullying	I feel safe at my school during the school day.
	I feel safe at my school before and after school hours.
	I feel safe going to or coming from my school.
	The rules for behavior are enforced at my school.
	There is enough room for students to learn at my school.
	Students at my school know the rules and what happens when students break the rules.

APPENDIX D

INFORMATION ABOUT OUTCOME INDICATORS

Table D.1 *College or career readiness school rating table*

Rating	COCR Percentage (%)
Excellent	80.0 – 100.0
Good	70.0-79.9
Average	60.0-69.9
Below Average	50.0-59.9
Unsatisfactory	0.0-49.9

Note. Adapted from SC Department of Education and SC EOC (2019)

Table D.2 *SC Ready rating table for elementary and middle school students*

Points	Level	Level Descriptor	
		SC Ready	Alternative Assessment
0	1	Does not meet expectations	Foundational
1	2	Approaches expectations	Emerging
2	3	Meets expectations	Meets
3	4	Exceeds expectations	Exceeds

Note. Adapted from SC Department of Education and SC EOC (2018)

Table D.3 *School-level ratings for academic accountability indicators*

Rating	Elementary		Middle		High	
	With ELP	Without ELP	With ELP	Without ELP	With ELP	Without ELP
Excellent	21.43-35.00	24.49-40.00	20.10-35.00	22.97-40.00	15.91-25.00	19.09-30.00
Good	18.55-21.42	21.19-24.48	16.72-20.09	19.11-22.96	13.45-15.90	16.14-19.08
Average	13.36-18.54	15.27-21.18	12.00-16.71	13.71-19.10	10.22-13.44	12.26-16.13
Below Average	9.62-13.35	10.99-15.26	8.37-11.99	9.57-13.70	7.22-10.21	8.66-12.25
Unsatisfactory	0.00-9.61	0.00-10.98	0.00-8.36	0.00-9.56	0.00-7.21	0.00-8.65

Note. Adapted from SC Department of Education and SC EOC (2018)

Table D.4 *EOCEP rating table for high school students*

Points	EOCEP Grade Level	Alternative Assessment Level Descriptor
0	F	Level 1: foundational
1	D	Level 2: emerging
2	C	Level 3: Meets
3	B	Level 4: Exceeds
4	A	

Note. Adapted from SC Department of Education and SC EOC (2018)

APPENDIX E

LOWER-LEVEL LPA MODEL FIT

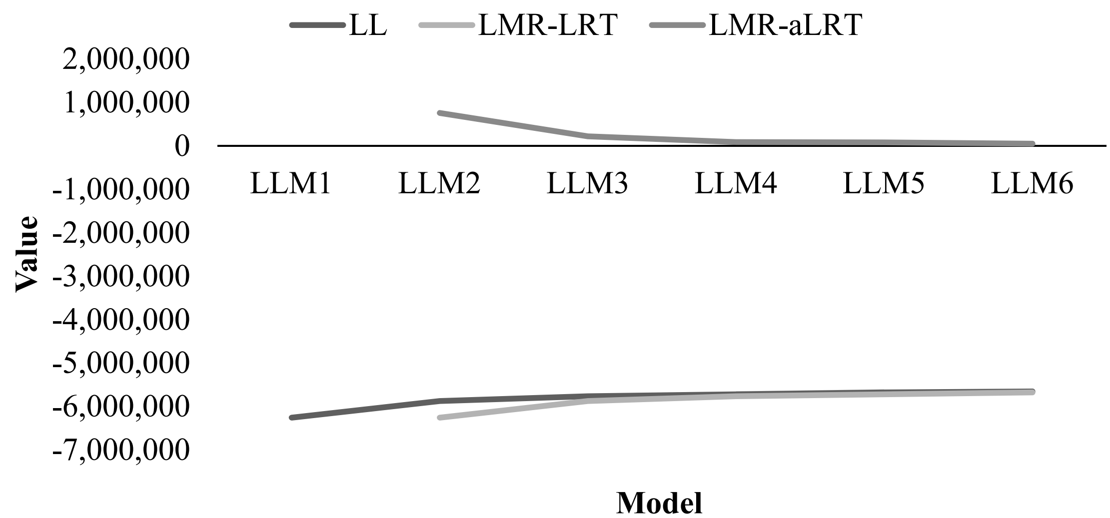

Figure E.1 *Absolute and relative fit indices for lower-level LPA models*

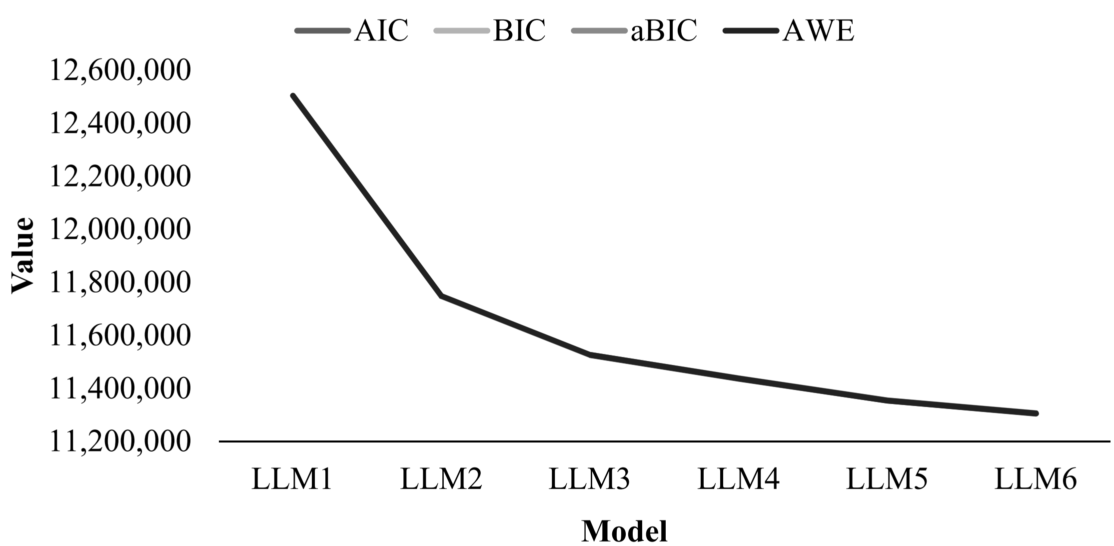

Figure E.2 *Information criterion for lower-level LPA models*

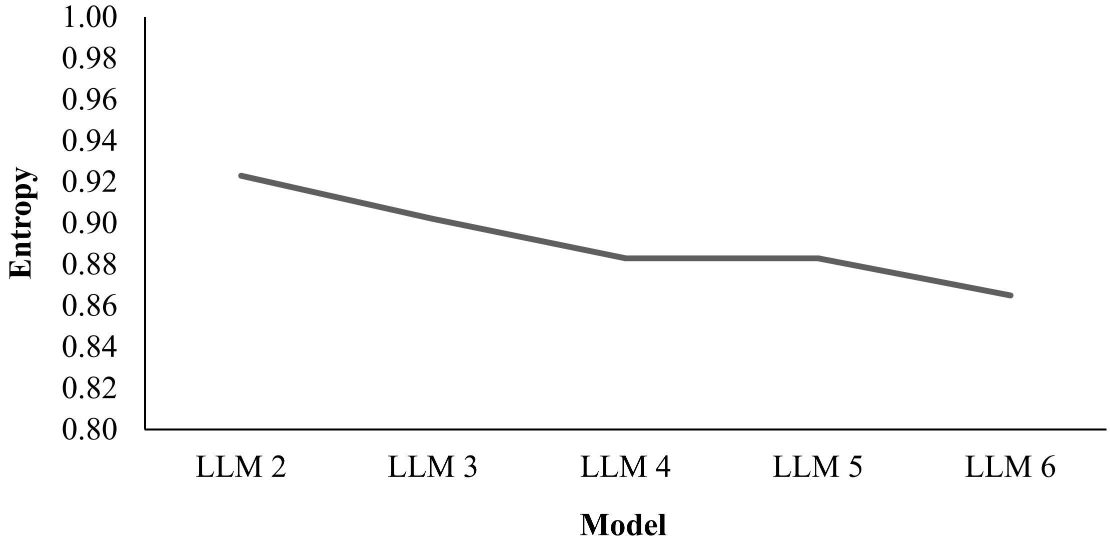

Figure E.3 *Entropy value by model*

APPENDIX F

ITEM-LEVEL INFORMATION FOR LLM4-LLM6

Table F.1 *Item-level information for LLM4-LLM6*

Model	Item	Profile											
		1		2		3		4		5		6	
		M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
LLM4	A2	-1.517	0.033	-0.475	0.013	0.02	0.009	0.462	0.004				
	A3	-1.619	0.049	-0.397	0.012	0.034	0.009	0.409	0.003				
	A4	-1.34	0.046	-0.341	0.01	0.016	0.008	0.362	0.003				
	A5	-1.577	0.023	-0.635	0.015	0.018	0.009	0.572	0.005				
	A6	-1.761	0.031	-0.593	0.015	0.032	0.009	0.552	0.004				
	A7	-1.387	0.028	-0.514	0.013	0.024	0.009	0.466	0.004				
	A8	-1.401	0.032	-0.44	0.012	**0.01**	**0.008**	0.438	0.004				
	A9	-1.489	0.042	-0.405	0.012	0.03	0.008	0.403	0.003				
	A10	-1.322	0.022	-0.488	0.012	-0.027	0.008	0.505	0.005				
	A11	-1.264	0.016	-0.605	0.013	-0.027	0.008	0.571	0.006				
	A12	-1.204	0.019	-0.534	0.012	-0.047	0.007	0.545	0.006				
	A13	-1.287	0.019	-0.535	0.012	-0.029	0.008	0.533	0.006				
	A15	-1.168	0.017	-0.511	0.011	-0.057	0.008	0.539	0.006				
	B1	-1.255	0.02	-0.666	0.015	-0.027	0.008	0.609	0.006				
	B2	-1.391	0.025	-0.666	0.016	**-0.003**	**0.008**	0.594	0.005				
	B3	-0.941	0.013	-0.611	0.011	-0.116	0.008	0.647	0.009				
	B4	-1.324	0.021	-0.648	0.013	-0.028	0.008	0.608	0.006				
	B6	-0.992	0.015	-0.64	0.013	-0.093	0.008	0.643	0.009				
	B7	-0.951	0.015	-0.634	0.012	-0.103	0.008	0.646	0.009				
	B11	-1.74	0.023	-0.853	0.023	0.1	0.009	0.625	0.004				
	B12	-1.784	0.023	-0.853	0.023	0.109	0.009	0.619	0.004				

Model	Item	Profile											
		1		2		3		4		5		6	
		M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
	B13	-1.705	0.03	-0.706	0.019	0.082	0.008	0.552	0.003				
	B14	-1.288	0.02	-0.642	0.015	-0.03	0.007	0.601	0.006				
	B15	-1.539	0.018	-0.752	0.016	**-0.005**	**0.008**	0.67	0.006				
	B16	-1.914	0.028	-0.739	0.016	0.047	0.01	0.643	0.004				
	B18	-1.677	0.02	-0.812	0.018	0.037	0.009	0.671	0.005				
	C1	-1.476	0.037	-0.499	0.012	**0.002**	**0.01**	0.495	0.004				
	C2	-1.586	0.05	-0.444	0.012	0.028	0.01	0.442	0.003				
	C3	-1.616	0.036	-0.546	0.012	0.025	0.01	0.513	0.004				
	C4	-1.15	0.022	-0.51	0.009	-0.047	0.009	0.523	0.005				
	C5	-1.081	0.028	-0.411	0.01	-0.017	0.009	0.415	0.004				
	C6	-1.789	0.05	-0.468	0.012	0.04	0.01	0.468	0.003				
	C7	-1.248	0.027	-0.46	0.01	**-0.01**	**0.008**	0.458	0.005				
	C8	-1.375	0.028	-0.509	0.011	**0.007**	**0.008**	0.483	0.004				
LLM5	A2	-1.439	0.026	-0.66	0.012	-0.06	0.016	0.47	0.004	0.1	0.006		
	A3	-1.501	0.038	-0.641	0.013	0.024	0.012	0.412	0.003	0.123	0.007		
	A4	-1.256	0.036	-0.511	0.012	-0.027	0.012	0.366	0.003	0.087	0.006		
	A5	-1.53	0.019	-0.696	0.014	-0.267	0.02	0.589	0.004	0.084	0.006		
	A6	-1.684	0.025	-0.717	0.014	-0.178	0.021	0.564	0.004	0.109	0.006		
	A7	-1.327	0.023	-0.62	0.012	-0.185	0.018	0.473	0.004	0.098	0.006		
	A8	-1.322	0.027	-0.552	0.011	-0.134	0.016	0.446	0.003	0.077	0.006		
	A9	-1.408	0.034	-0.577	0.012	-0.049	0.014	0.408	0.003	0.106	0.006		
	A10	-1.284	0.019	-0.586	0.011	-0.139	0.017	0.524	0.005	0.028	0.006		
	A11	-1.226	0.014	-0.568	0.013	-0.392	0.018	0.594	0.005	0.022	0.006		
	A12	-1.182	0.017	-0.417	0.012	-0.436	0.016	0.576	0.005	-0.023	0.005		
	A13	-1.251	0.016	-0.539	0.011	-0.299	0.018	0.556	0.005	0.019	0.006		
	A15	-1.137	0.015	-0.516	0.01	-0.3	0.016	0.563	0.006	**-0.009**	**0.006**		

Model	Item	Profile											
		1		2		3		4		5		6	
		M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
	B1	-1.236	0.017	-0.328	0.015	-0.827	0.018	0.647	0.005	**-0.012**	**0.007**		
	B2	-1.369	0.021	-0.342	0.015	-0.802	0.02	0.626	0.004	0.02	0.007		
	B3	-0.94	0.011	-0.339	0.013	-0.735	0.013	0.699	0.007	-0.105	0.007		
	B4	-1.302	0.018	-0.427	0.013	-0.684	0.016	0.639	0.005	**0.009**	**0.006**		
	B6	-0.991	0.012	-0.344	0.014	-0.773	0.013	0.694	0.007	-0.083	0.007		
	B7	-0.951	0.012	-0.333	0.014	-0.781	0.012	0.699	0.007	-0.094	0.007		
	B11	-1.795	0.021	-0.199	0.011	-1.635	0.019	0.655	0.003	0.194	0.007		
	B12	-1.835	0.021	-0.209	0.011	-1.619	0.019	0.647	0.003	0.206	0.007		
	B13	-1.7	0.027	-0.226	0.009	-1.238	0.021	0.575	0.003	0.157	0.006		
	B14	-1.275	0.017	-0.342	0.013	-0.785	0.015	0.636	0.005	**-0.003**	**0.006**		
	B15	-1.512	0.016	-0.504	0.014	-0.76	0.018	0.702	0.005	0.037	0.006		
	B16	-1.835	0.022	-0.752	0.014	-0.419	0.021	0.661	0.003	0.127	0.007		
	B18	-1.66	0.017	-0.507	0.015	-0.878	0.019	0.697	0.004	0.089	0.006		
	C1	-1.41	0.029	-0.736	0.013	**-0.015**	**0.015**	0.504	0.004	0.091	0.007		
	C2	-1.491	0.039	-0.666	0.014	**-0.018**	**0.014**	0.447	0.003	0.116	0.007		
	C3	-1.546	0.029	-0.716	0.013	-0.118	0.015	0.523	0.003	0.11	0.007		
	C4	-1.119	0.018	-0.596	0.01	-0.204	0.015	0.54	0.005	0.016	0.007		
	C5	-1.043	0.024	-0.554	0.011	-0.088	0.014	0.424	0.004	0.051	0.007		
	C6	-1.697	0.04	-0.677	0.013	-0.03	0.013	0.474	0.003	0.127	0.007		
	C7	-1.194	0.022	-0.54	0.01	-0.182	0.014	0.471	0.004	0.05	0.006		
	C8	-1.323	0.023	-0.525	0.011	-0.292	0.015	0.496	0.004	0.066	0.006		
LLM6	A2	-1.507	0.029	-0.716	0.015	-0.08	0.016	-0.24	0.017	0.248	0.008	0.453	0.004
	A3	-1.611	0.042	-0.634	0.017	**0.004**	**0.013**	-0.251	0.025	0.263	0.005	0.409	0.003
	A4	-1.361	0.039	-0.501	0.016	-0.053	0.013	-0.203	0.021	0.19	0.006	0.362	0.003
	A5	-1.572	0.021	-0.853	0.017	-0.275	0.019	-0.148	0.011	0.172	0.009	0.554	0.004
	A6	-1.757	0.028	-0.84	0.016	-0.183	0.02	-0.199	0.014	0.234	0.009	0.538	0.004

Model	Item	Profile											
		1		2		3		4		5		6	
		M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
	A7	-1.38	0.027	-0.694	0.014	-0.205	0.017	-0.179	0.015	0.193	0.007	0.459	0.004
	A8	-1.389	0.03	-0.617	0.014	-0.148	0.015	-0.196	0.015	0.188	0.007	0.43	0.004
	A9	-1.506	0.037	-0.595	0.016	-0.072	0.014	-0.211	0.02	0.227	0.006	0.4	0.003
	A10	-1.324	0.02	-0.703	0.013	-0.147	0.016	-0.181	0.009	0.129	0.01	0.485	0.004
	A11	-1.254	0.017	-0.738	0.014	-0.396	0.017	-0.076	0.008	0.033	0.009	0.551	0.005
	A12	-1.228	0.018	-0.607	0.014	-0.424	0.016	0.061	0.008	-0.139	0.01	0.532	0.005
	A13	-1.29	0.018	-0.675	0.013	-0.305	0.017	-0.125	0.008	0.072	0.009	0.512	0.005
	A15	-1.171	0.016	-0.644	0.012	-0.301	0.016	-0.125	0.008	0.029	0.01	0.514	0.005
	B1	-1.289	0.019	-0.576	0.017	-0.787	0.017	0.27	0.008	-0.353	0.029	0.628	0.005
	B2	-1.434	0.022	-0.569	0.018	-0.76	0.019	0.219	0.01	-0.266	0.027	0.61	0.004
	B3	-0.961	0.012	-0.571	0.014	-0.707	0.012	0.256	0.009	-0.496	0.026	0.67	0.007
	B4	-1.363	0.018	-0.618	0.014	-0.667	0.016	0.116	0.009	-0.188	0.018	0.611	0.004
	B6	-1.016	0.014	-0.627	0.016	-0.752	0.012	0.328	0.014	-0.497	0.022	0.666	0.007
	B7	-0.975	0.014	-0.616	0.017	-0.763	0.012	0.337	0.015	-0.521	0.022	0.67	0.008
	B11	-1.909	0.019	-0.313	0.015	-1.788	0.015	0.055	0.013	0.194	0.011	0.631	0.003
	B12	-1.955	0.019	-0.319	0.015	-1.769	0.016	0.057	0.014	0.205	0.011	0.625	0.003
	B13	-1.855	0.028	-0.277	0.013	-1.396	0.022	**-0.013**	**0.015**	0.19	0.009	0.556	0.003
	B14	-1.331	0.018	-0.554	0.015	-0.779	0.015	0.145	0.007	-0.2	0.016	0.601	0.005
	B15	-1.56	0.017	-0.738	0.017	-0.761	0.018	0.093	0.007	-0.104	0.014	0.663	0.004
	B16	-1.914	0.026	-0.909	0.015	-0.433	0.02	-0.145	0.014	0.206	0.008	0.631	0.003
	B18	-1.714	0.018	-0.724	0.016	-0.899	0.019	0.034	0.008	0.026	0.011	0.662	0.003
	C1	-1.495	0.03	-0.76	0.017	-0.046	0.016	-0.327	0.022	0.288	0.008	0.487	0.004
	C2	-1.616	0.041	-0.648	0.02	-0.056	0.015	-0.291	0.028	0.278	0.006	0.444	0.003
	C3	-1.643	0.03	-0.766	0.016	-0.15	0.017	-0.257	0.022	0.259	0.007	0.508	0.003
	C4	-1.166	0.019	-0.676	0.011	-0.224	0.015	-0.21	0.012	0.113	0.009	0.504	0.005
	C5	-1.108	0.025	-0.566	0.014	-0.117	0.015	-0.268	0.017	0.201	0.008	0.407	0.004

Model	Item	Profile											
		1		2		3		4		5		6	
		M	SE	M	SE	M	SE	M	SE	M	SE	M	SE
	C6	-1.849	0.041	-0.674	0.018	-0.064	0.015	-0.29	0.027	0.302	0.006	0.467	0.003
	C7	-1.273	0.024	-0.594	0.012	-0.206	0.015	-0.196	0.016	0.147	0.008	0.45	0.004
	C8	-1.403	0.025	-0.606	0.013	-0.315	0.016	-0.163	0.015	0.148	0.008	0.476	0.004

Note. Statistically insignificant values are in bold. M = mean; SE=standard error

APPENDIX G

ITEM BY FACTOR GUIDE

Table G.1 *Item by factor guide*

Analysis Item Number	Factor	Survey Item Text
A2	LE	My teachers want me to understand what I am learning, not just remember facts.
A3	LE	My teachers expect students to learn.
A4	LE	My teachers expect students to behave.
A5	LE	My teachers spend enough time helping me learn.
A6	LE	My teachers help students when they do not understand something.
A7	LE	My teachers do a good job teaching me mathematics.
A8	LE	My teachers do a good job teaching me English language arts.
A9	LE	My teachers give tests on what I learn in class.
A10	LE	My teachers give homework assignments that help me learn better.
A11	LE	My classes are interesting and fun.
A12	SPE	Students at my school believe they can do good work.
A13	LE	My teachers praise students when they do good work.
A15	LE	The textbooks and workbooks I use at my school really help me to learn.
B1	SPE	The grounds around my school are kept clean.
B2	SPE	The hallways at my school are kept clean.
B3	SPE	The bathrooms at my school are kept clean.
B4	SPE	Broken things at my school get fixed.

Analysis Item Number	Factor	Survey Item Text
B6	SPE	Students at my school behave well in class.
B7	SPE	Students at my school behave well in the hallways, in the lunchroom, and on school grounds
B11	SA	I feel safe at my school before and after school hours.
B12	SA	I feel safe at my school during the school day.
B13	SA	I feel safe going to or coming from my school.
B14	SPE	Students from different backgrounds get along well at my school.
B15	SPE	Teachers and students get along well with each other at my school.
B16	LE	Teachers work together to help students at my school.
B18	SPE	I am satisfied with the social and physical environment at my school.
C1	HSR	My parent knows what I am expected to learn at school.
C2	HSR	My parent knows how well I am doing in school.
C3	HSR	My school informs parents about school programs and activities.
C4	HSR	Parents at my school know their children's homework assignments.
C5	HSR	My parent helps me with my homework when I need it.
C6	HSR	Parents are welcomed at my school.
C7	HSR	Parents volunteer and participate in activities at my school.
C8	HSR	I am satisfied with home-school relations.

Note. Factor names are LE="Learning Environment", SP="Social-Physical Environment", HS="Home-School Relations."

Appendix H

ITEM-LEVEL GRAPHS OF REJECTED LOWER-LEVEL MODELS

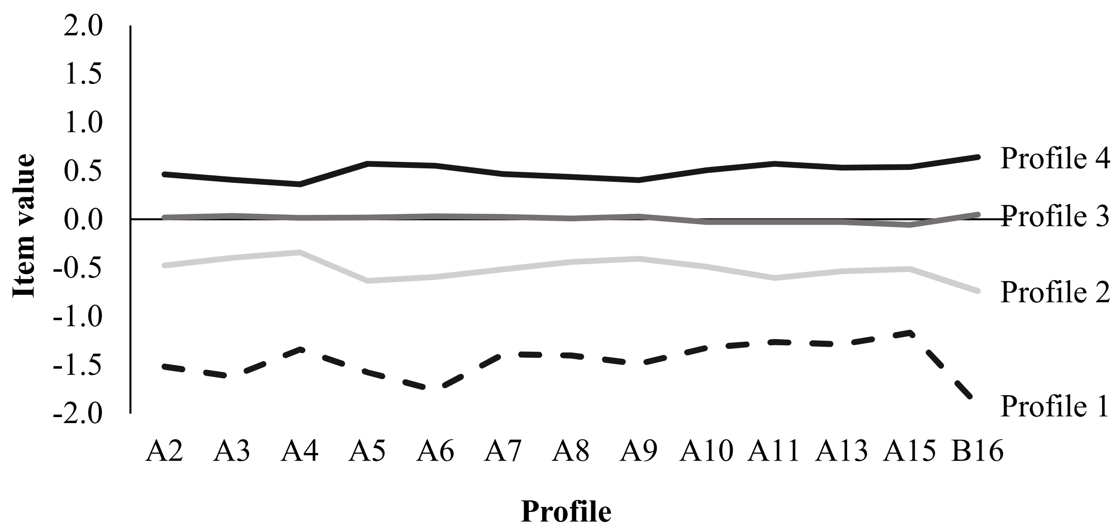

Figure H.1 *Learning Environment Domain, four-profile lower-level model*

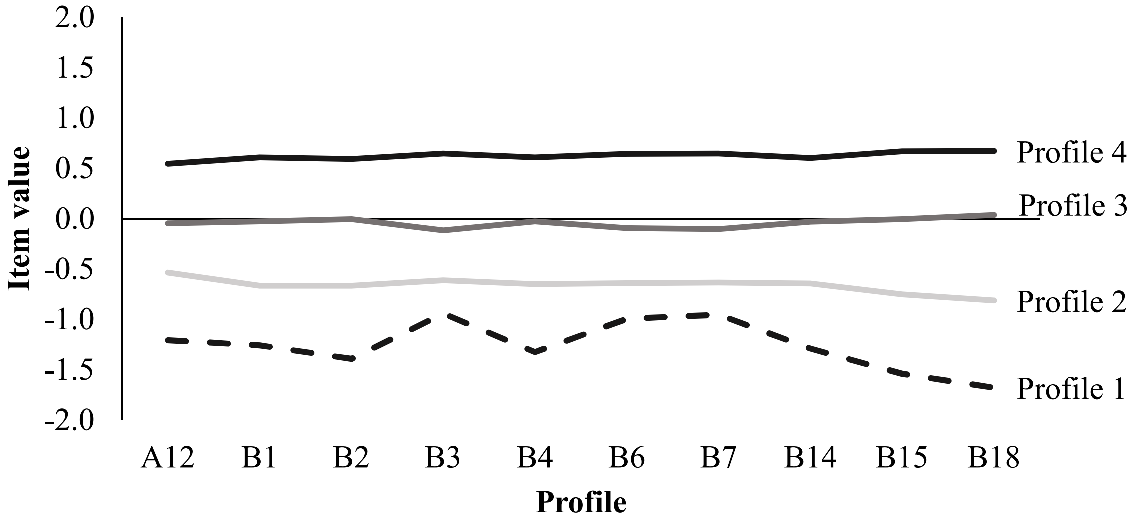

Figure H.2 *Social/Physical Environment Domain, Four-Profile lower-level model*

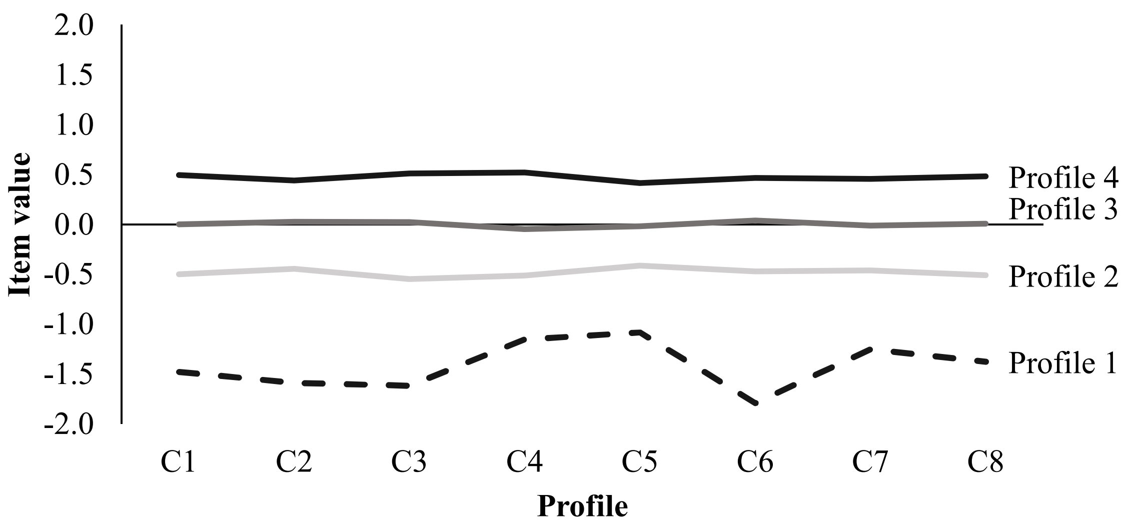

Figure H.3 *Home-School Relationship Domain, Four-Profile lower-level model*

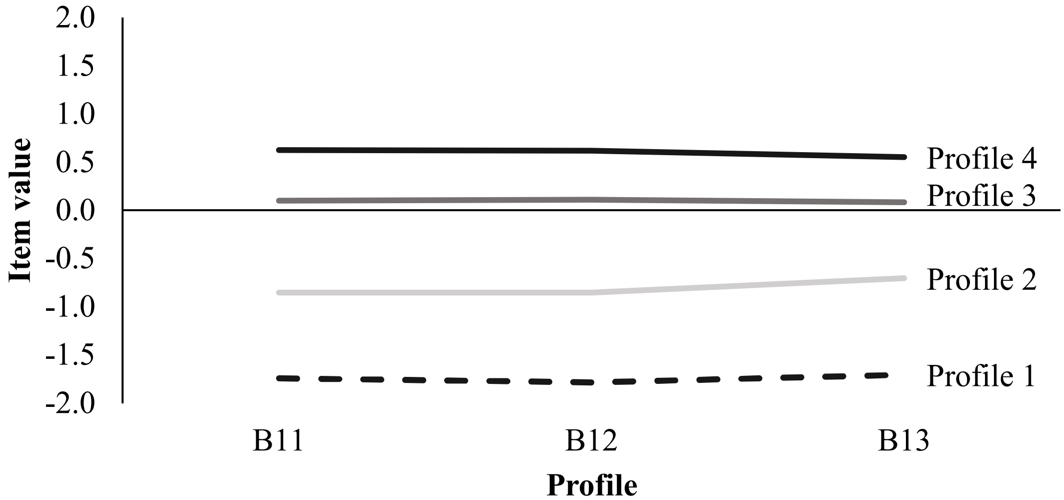

Figure H.4 *Safety Domain, Four-Profile lower-level model*

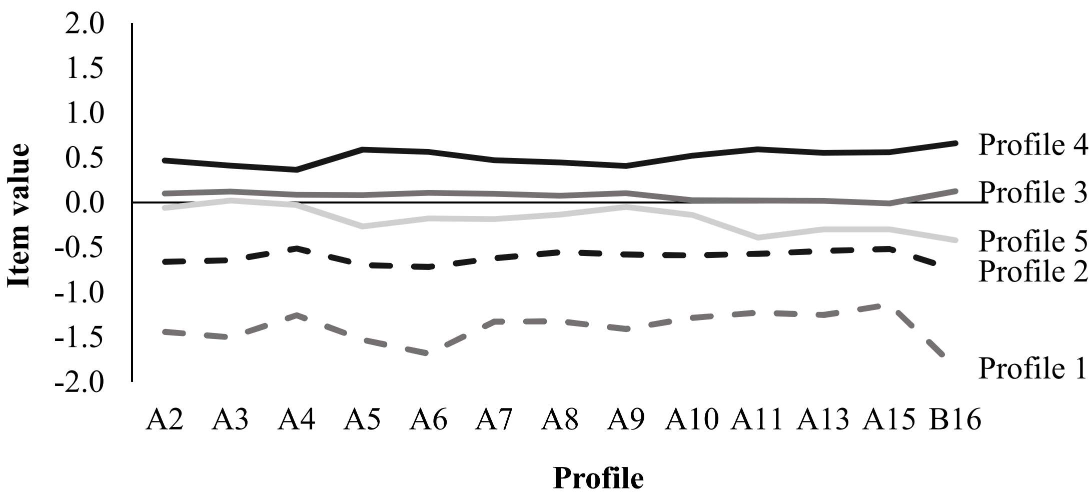

Figure H.5 *Learning Environment Domain, five-profile lower-level model*

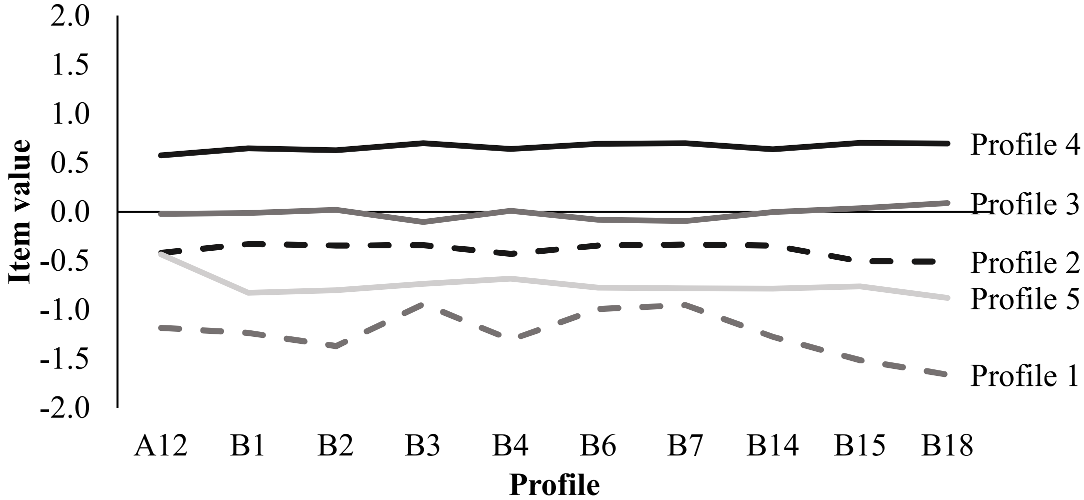

Figure H.6 *Social/Physical Environment Domain, Five-Profile lower-level model*

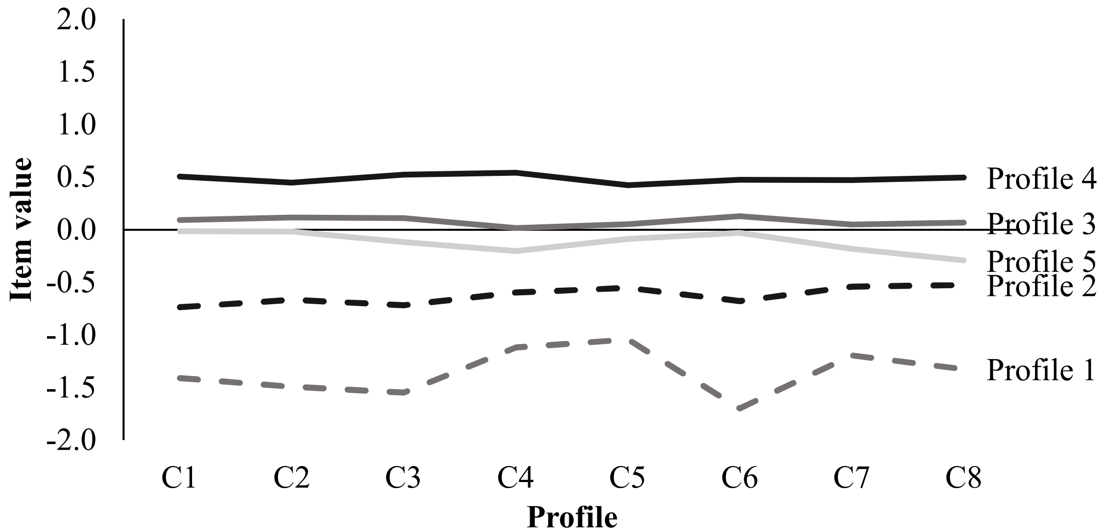

Figure H.7 *Home-School Relationship Domain, Five-Profile lower-level model*

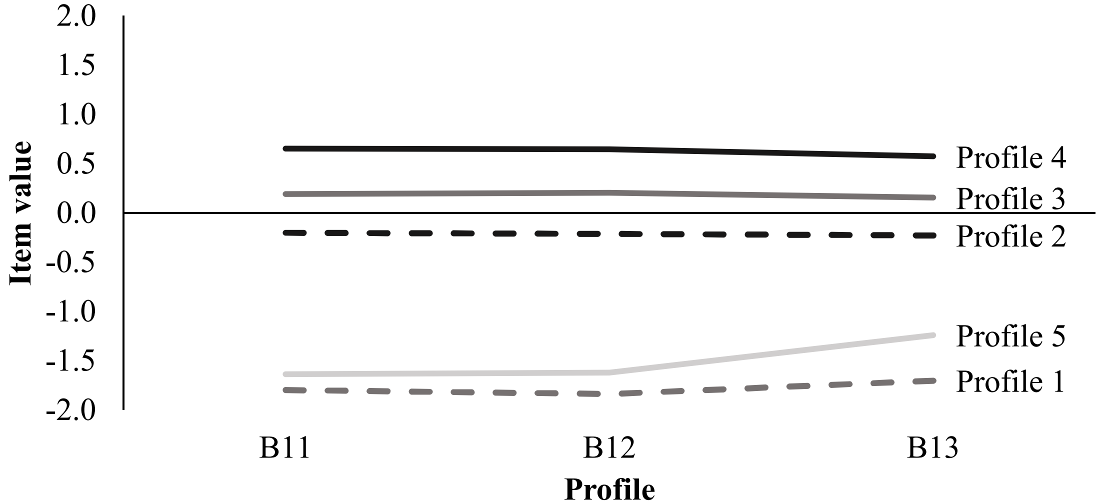

Figure H.8 *Safety Domain, Five-Profile lower-level model*

APPENDIX I

WITHIN-PROFILE ITEM RANKINGS FOR LLM6

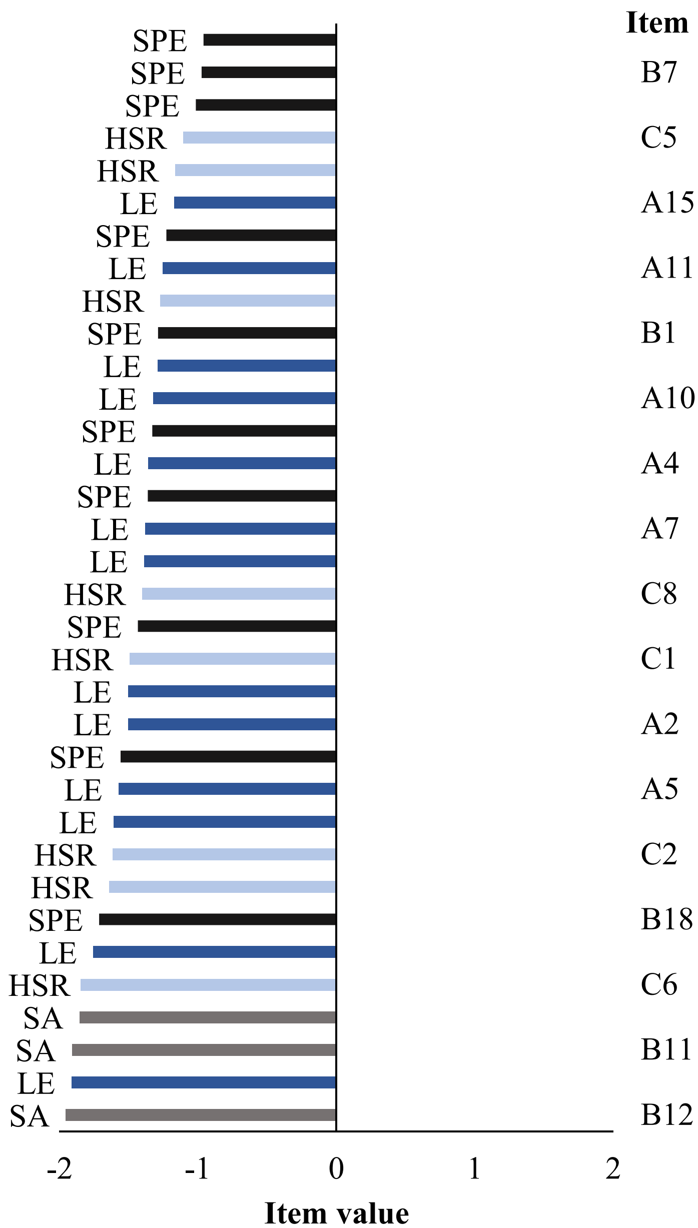

Figure I.1 *Profile 1 Item Rankings*

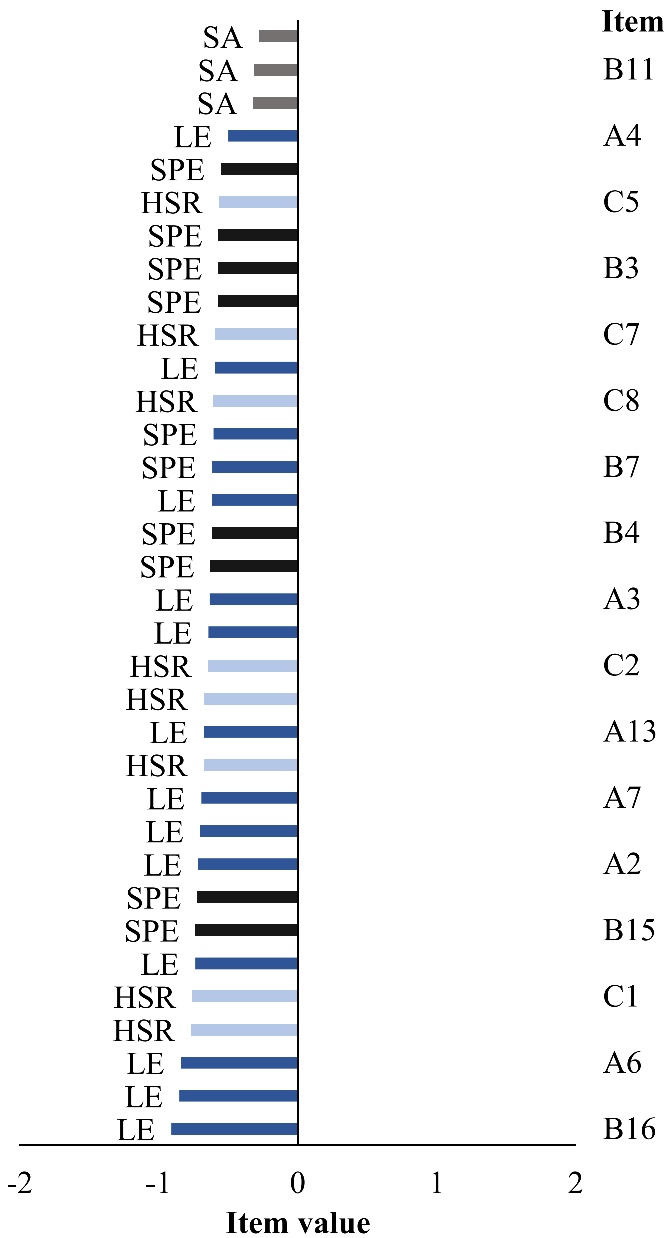

Figure I.2 *Profile 2 Item Rankings*

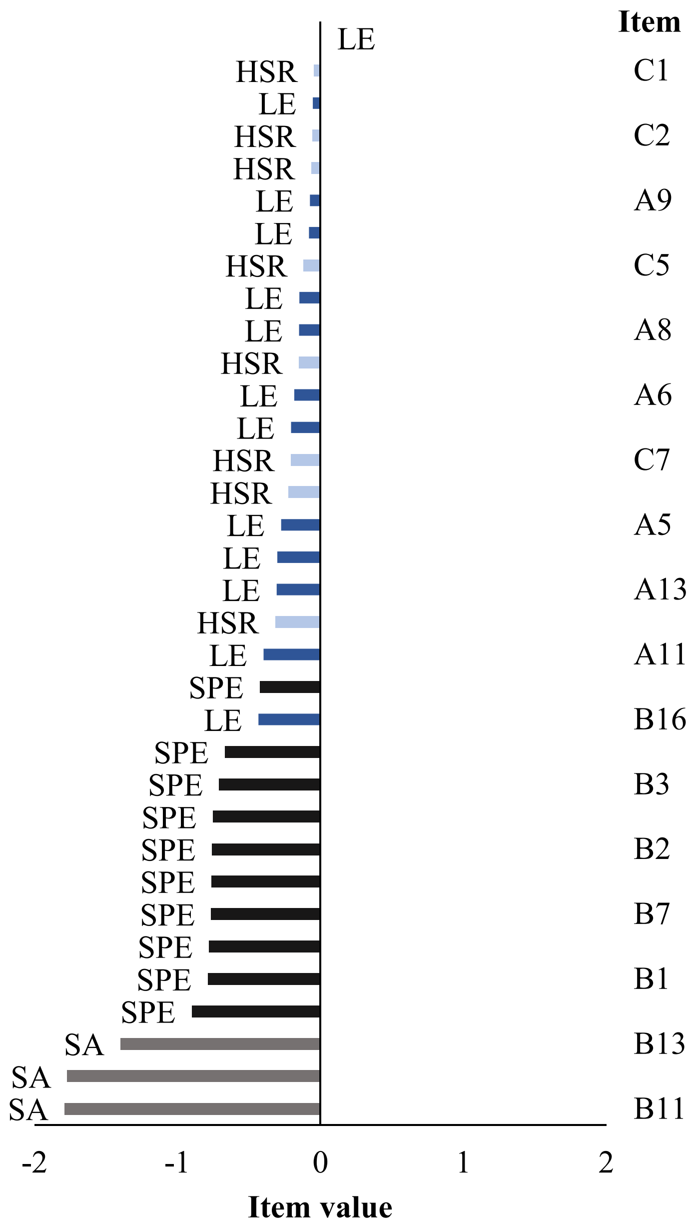

Figure I.3 *Profile 3 Item Rankings*

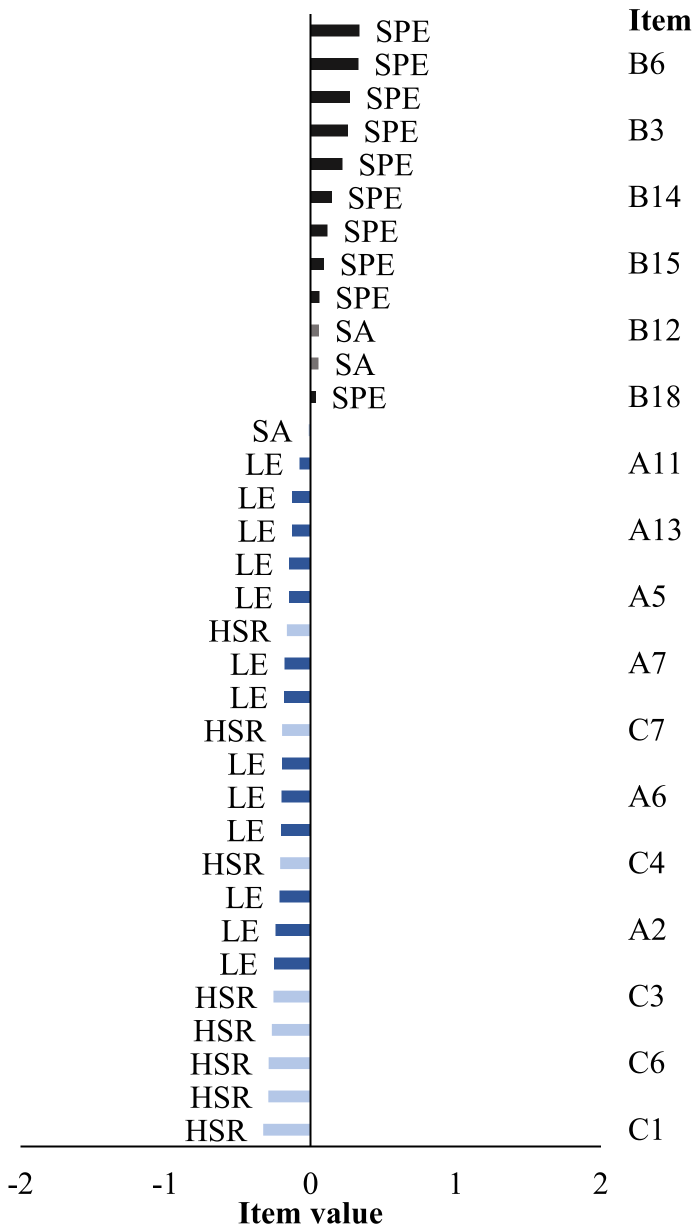

Figure I.4 *Profile 4 Item Rankings*

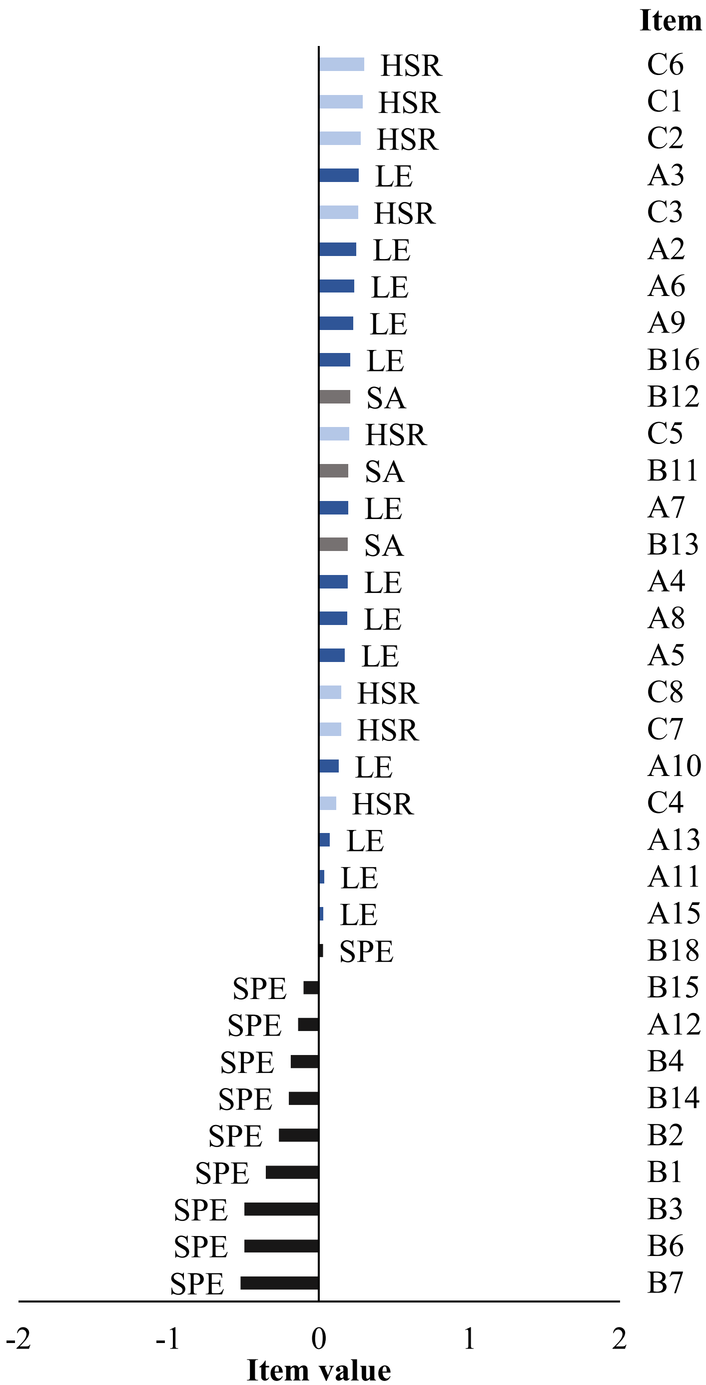

Figure I.5 Profile 5 Item Rankings

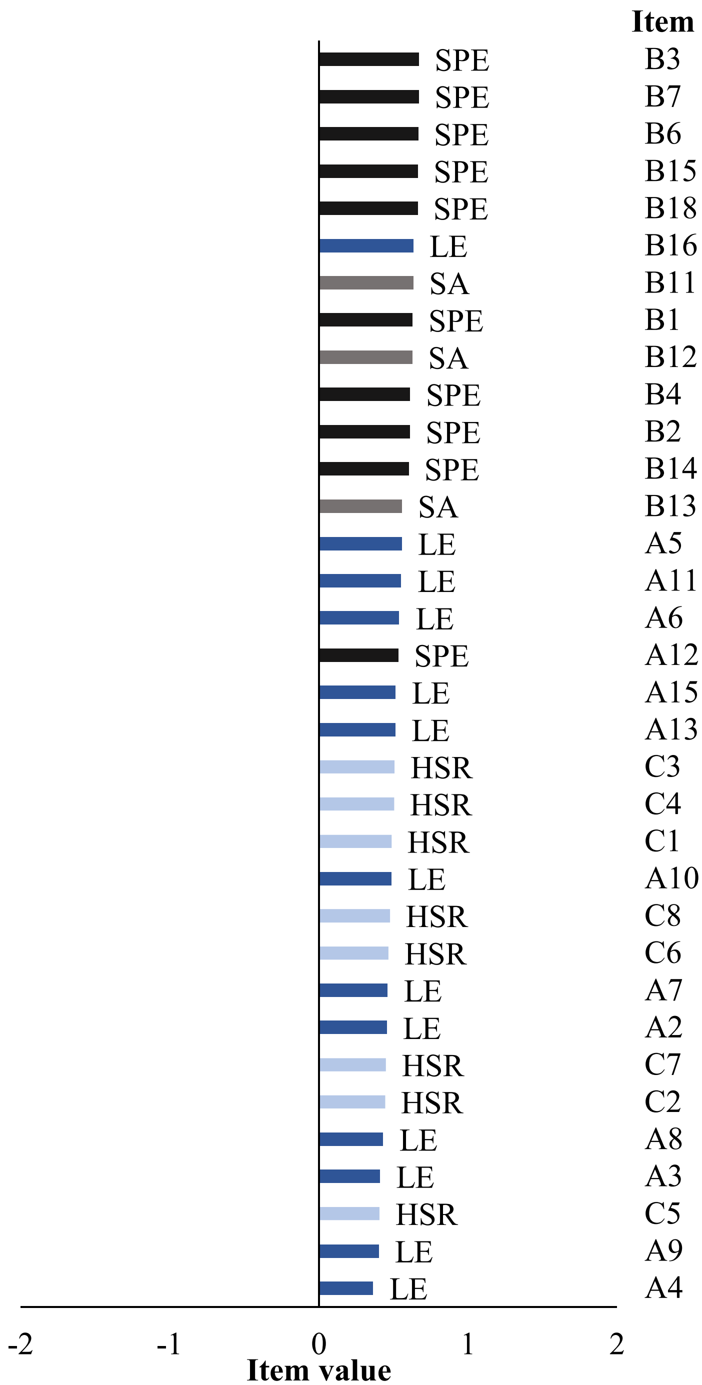

Figure I.6 *Profile 6 Item Rankings*

APPENDIX J

PLOTS FOR UPPER-LEVEL MODEL FIT INDICES

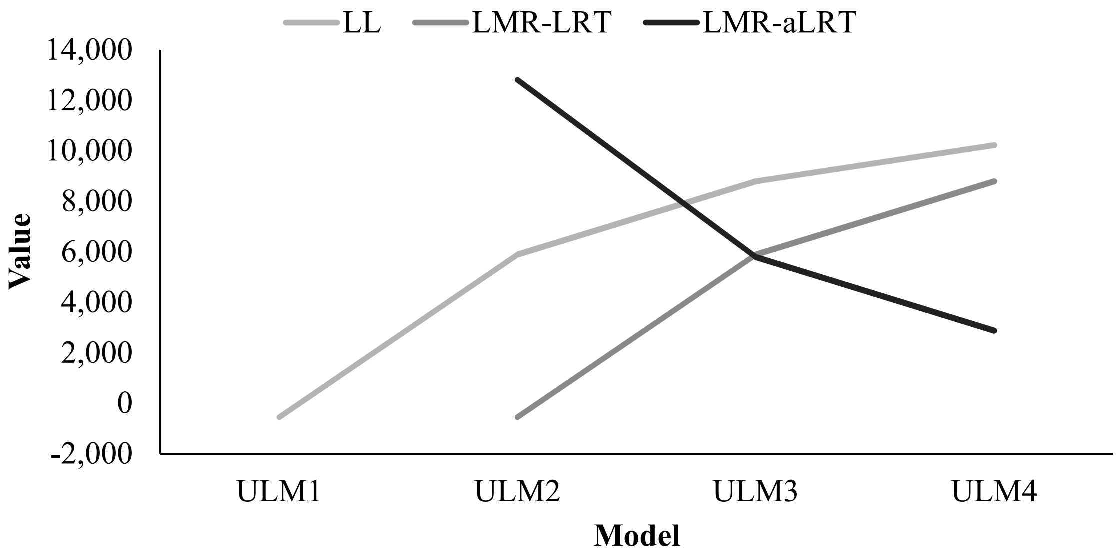

Figure J.1 *Absolute and relative fit indices for lower-level models.*

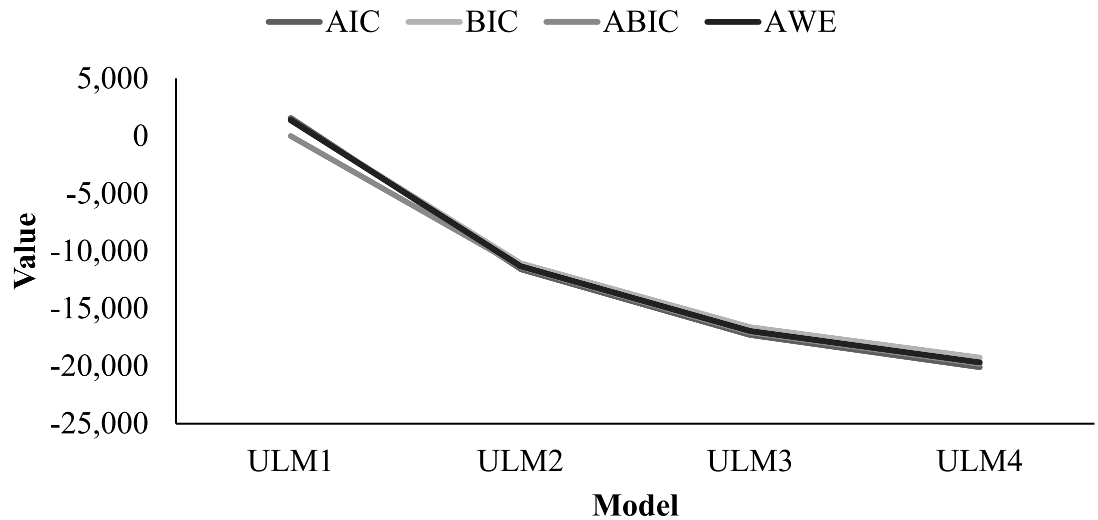

Figure J.2 *Information criteria for upper-level models*

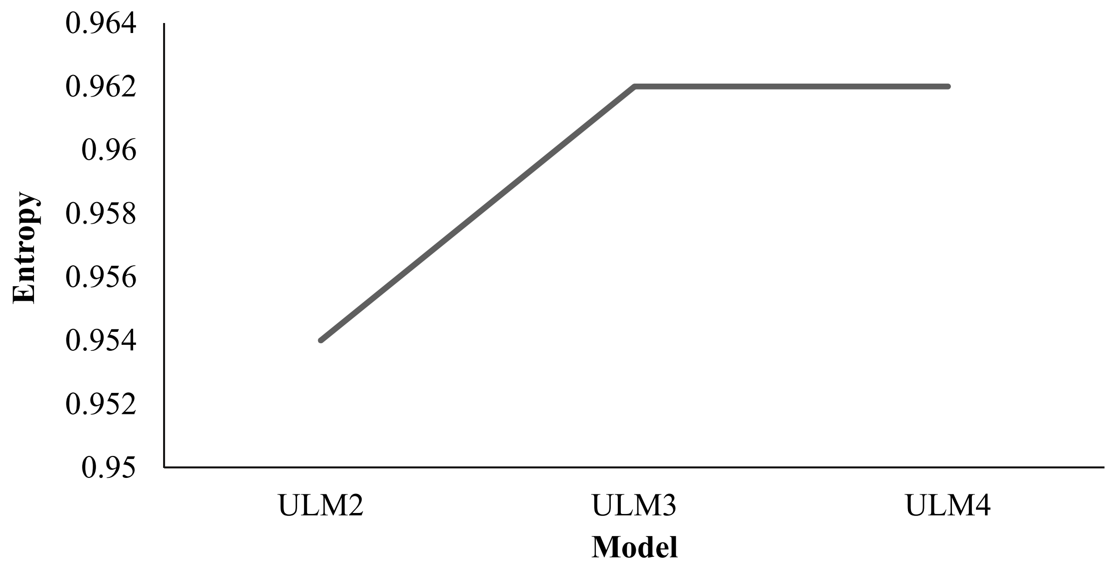

Figure J.3 *Entropy for upper-level models*

APPENDIX K

ITEM-LEVEL INFORMATION FOR ULM 2-ULM4

Table K.1 *Item-level information for ULM2-ULM4*

Model	Item	Profile							
		1		2		3		4	
		M	SE	M	SE	M	SE	M	SE
ULM2	A2	0.111	0.012	-0.088	0.013				
	A3	0.098	0.011	-0.116	0.014				
	A4	0.096	0.010	-0.126	0.016				
	A5	0.135	0.014	-0.126	0.016				
	A6	0.132	0.013	-0.123	0.016				
	A7	0.108	0.014	-0.128	0.017				
	A8	0.097	0.011	-0.101	0.016				
	A9	0.092	0.011	-0.118	0.016				
	A10	0.099	0.016	-0.066	0.014				
	A11	0.129	0.015	-0.108	0.014				
	A12	0.149	0.018	-0.130	0.014				
	A13	0.128	0.015	-0.096	0.014				
	A15	0.093	0.014	**-0.013**	0.011				
	B1	0.234	0.026	-0.259	0.027				
	B2	0.220	0.023	-0.241	0.027				
	B3	0.254	0.032	-0.244	0.025				
	B4	0.191	0.023	-0.215	0.022				
	B6	0.210	0.026	-0.239	0.022				
	B7	0.207	0.025	-0.212	0.020				
	B11	0.178	0.017	-0.193	0.022				

Model	Item	Profile							
		1		2		3		4	
		M	SE	M	SE	M	SE	M	SE
	B12	0.178	0.017	-0.196	0.023				
	B13	0.145	0.015	-0.161	0.018				
	B14	0.179	0.022	-0.205	0.020				
	B15	0.197	0.022	-0.230	0.023				
	B16	0.157	0.016	-0.153	0.018				
	B18	0.171	0.019	-0.178	0.018				
	C1	0.090	0.011	-0.074	0.011				
	C2	0.095	0.012	-0.127	0.014				
	C3	0.118	0.013	-0.121	0.014				
	C4	0.111	0.013	-0.115	0.015				
	C5	0.076	0.010	-0.071	0.010				
	C6	0.103	0.011	-0.088	0.013				
	C7	0.114	0.015	-0.136	0.014				
	C8	0.117	0.013	-0.133	0.014				
ULM3	A2	-0.141	0.015	**0.014**	0.015	0.183	0.015		
	A3	-0.183	0.023	**0.004**	0.011	0.164	0.013		
	A4	-0.199	0.024	**0.000**	0.012	0.163	0.012		
	A5	-0.203	0.017	**0.016**	0.018	0.22	0.016		
	A6	-0.205	0.020	**0.019**	0.016	0.215	0.017		
	A7	-0.215	0.020	**0.010**	0.018	0.183	0.017		
	A8	-0.169	0.018	**0.009**	0.016	0.165	0.013		
	A9	-0.188	0.021	**0.000**	0.014	0.161	0.014		
	A10	-0.089	0.020	**-0.004**	0.015	0.186	0.024		
	A11	-0.181	0.017	**0.019**	0.017	0.212	0.018		
	A12	-0.213	0.016	**0.017**	0.018	0.253	0.022		
	A13	-0.154	0.017	**0.008**	0.015	0.231	0.018		
	A15	-0.044	0.017	**0.025**	0.014	0.171	0.024		
	B1	-0.411	0.047	**0.014**	0.024	0.390	0.026		

Model	Item	Profile							
		1		2		3		4	
		M	SE	M	SE	M	SE	M	SE
	B2	-0.39	0.048	**0.021**	0.022	0.357	0.024		
	B3	-0.379	0.039	**0.007**	0.026	0.444	0.038		
	B4	-0.345	0.031	**0.009**	0.022	0.327	0.028		
	B6	-0.363	0.032	**-0.005**	0.023	0.370	0.033		
	B7	-0.324	0.028	**0.002**	0.022	0.359	0.032		
	B11	-0.305	0.029	**0.010**	0.020	0.301	0.021		
	B12	-0.317	0.031	**0.012**	0.020	0.299	0.021		
	B13	-0.251	0.023	**0.006**	0.017	0.243	0.018		
	B14	-0.322	0.032	**0.004**	0.020	0.307	0.024		
	B15	-0.365	0.037	**0.009**	0.024	0.329	0.019		
	B16	-0.244	0.025	**0.011**	0.017	0.268	0.018		
	B18	-0.287	0.027	**0.013**	0.019	0.289	0.019		
	C1	-0.115	0.014	**0.003**	0.010	0.163	0.016		
	C2	-0.194	0.021	**-0.004**	0.012	0.165	0.015		
	C3	-0.194	0.021	**0.002**	0.013	0.213	0.015		
	C4	-0.193	0.025	**0.009**	0.011	0.193	0.019		
	C5	-0.104	0.015	**0.005**	0.008	0.122	0.015		
	C6	-0.138	0.020	**0.006**	0.010	0.178	0.014		
	C7	-0.205	0.029	**0.006**	0.013	0.178	0.014		
	C8	-0.205	0.022	**-0.002**	0.013	0.207	0.015		
ULM4	A2	0.038	0.010	-0.054	0.010	0.217	0.020	-0.208	0.022
	A3	0.035	0.010	-0.078	0.010	0.183	0.013	-0.263	0.020
	A4	0.038	0.010	-0.087	0.010	0.179	0.011	-0.29	0.021
	A5	0.055	0.011	-0.097	0.010	0.253	0.020	-0.262	0.023
	A6	0.055	0.010	-0.088	0.012	0.247	0.020	-0.280	0.023
	A7	0.037	0.012	-0.097	0.014	0.210	0.025	-0.261	0.025
	A8	0.044	0.010	-0.071	0.013	0.183	0.016	-0.247	0.026
	A9	0.035	0.009	-0.081	0.013	0.177	0.015	-0.275	0.021

Model	Item	Profile							
		1		2		3		4	
		M	SE	M	SE	M	SE	M	SE
	A10	**0.017**	0.015	-0.045	0.017	0.219	0.024	-0.119	0.031
	A11	0.053	0.012	-0.080	0.012	0.246	0.023	-0.240	0.022
	A12	0.059	0.011	-0.101	0.012	0.291	0.024	-0.277	0.019
	A13	0.044	0.012	-0.074	0.012	0.258	0.021	-0.197	0.023
	A15	**0.023**	0.013	**-0.003**	0.015	0.206	0.033	**-0.028**	0.023
	B1	0.113	0.022	-0.201	0.019	0.427	0.023	-0.583	0.025
	B2	0.109	0.019	-0.174	0.019	0.391	0.021	-0.579	0.031
	B3	0.106	0.027	-0.199	0.020	0.492	0.034	-0.515	0.025
	B4	0.083	0.019	-0.170	0.016	0.360	0.021	-0.464	0.025
	B6	0.084	0.016	-0.203	0.018	0.423	0.031	-0.489	0.022
	B7	0.084	0.015	-0.177	0.016	0.413	0.032	-0.446	0.022
	B11	0.084	0.014	-0.147	0.013	0.333	0.015	-0.451	0.020
	B12	0.084	0.013	-0.142	0.014	0.331	0.016	-0.479	0.022
	B13	0.069	0.012	-0.123	0.012	0.272	0.013	-0.376	0.019
	B14	0.081	0.013	-0.159	0.016	0.345	0.025	-0.471	0.022
	B15	0.096	0.013	-0.177	0.018	0.364	0.020	-0.535	0.023
	B16	0.064	0.012	-0.112	0.011	0.297	0.019	-0.341	0.021
	B18	0.073	0.012	-0.133	0.011	0.323	0.020	-0.400	0.021
	C1	0.026	0.010	-0.050	0.009	0.186	0.016	-0.159	0.018
	C2	0.034	0.009	-0.092	0.011	0.187	0.013	-0.283	0.019
	C3	0.038	0.011	-0.083	0.009	0.239	0.015	-0.274	0.017
	C4	0.042	0.011	-0.073	0.010	0.218	0.019	-0.294	0.020
	C5	0.028	0.011	-0.044	0.009	0.133	0.014	-0.151	0.019
	C6	0.039	0.010	-0.059	0.009	0.199	0.014	-0.205	0.019
	C7	0.053	0.013	-0.094	0.010	0.196	0.016	-0.312	0.018
	C8	0.042	0.011	-0.104	0.009	0.234	0.014	-0.280	0.015

Note. All values are statistically significant ($p<0.05$) with the exception of those in bold.

APPENDIX L

ITEM-LEVEL GRAPHS FOR REJECTED UPPER-LEVEL MODELS

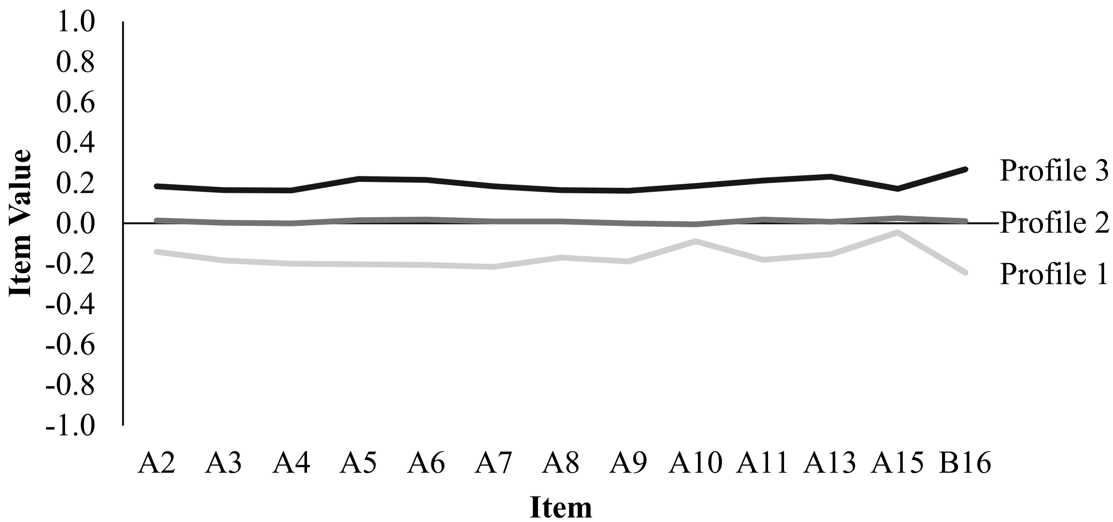

Figure L.1 *Learning environment domain, three-profile upper-level model*

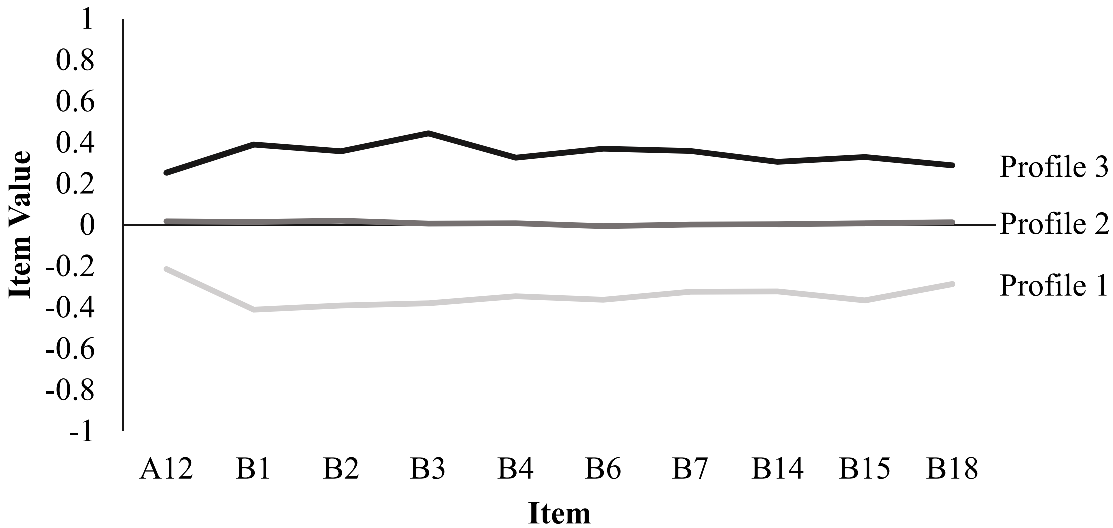

Figure L.2 *Social/physical environment domain, three-profile upper-level model*

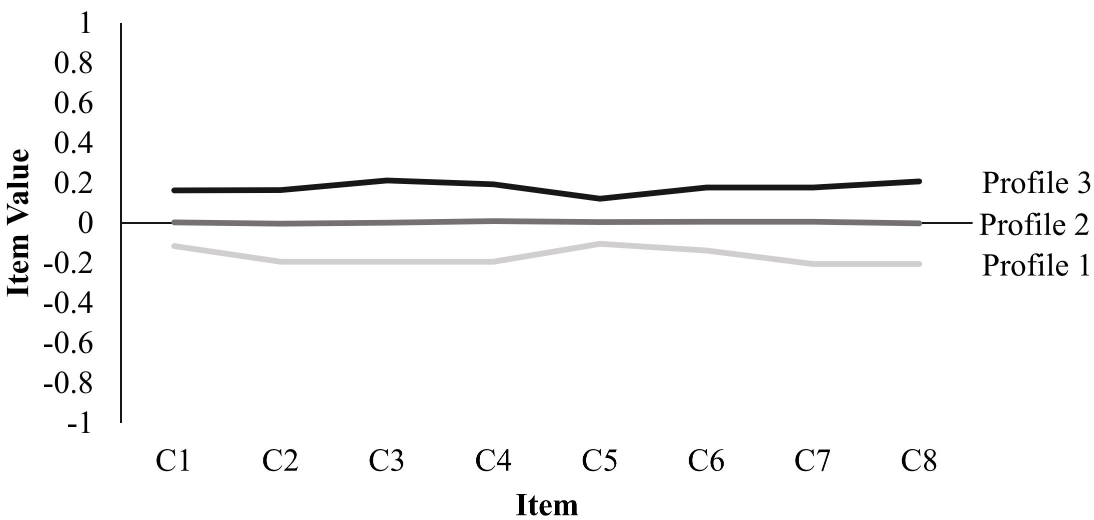

Figure L.3 *Home-school relationship domain, three-profile upper-level model*

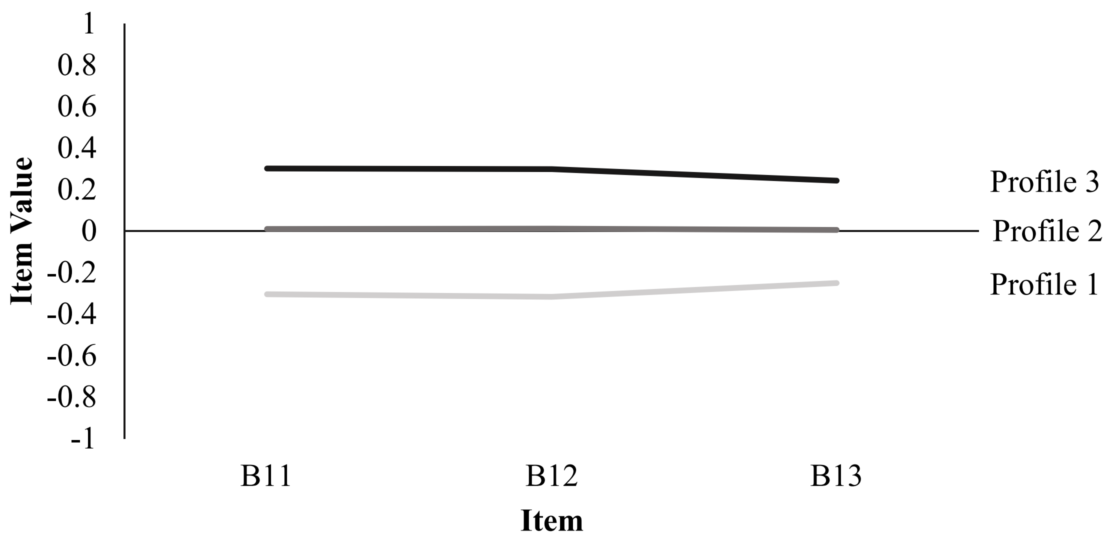

Figure L.4 *Safety domain, three-profile upper-level model*

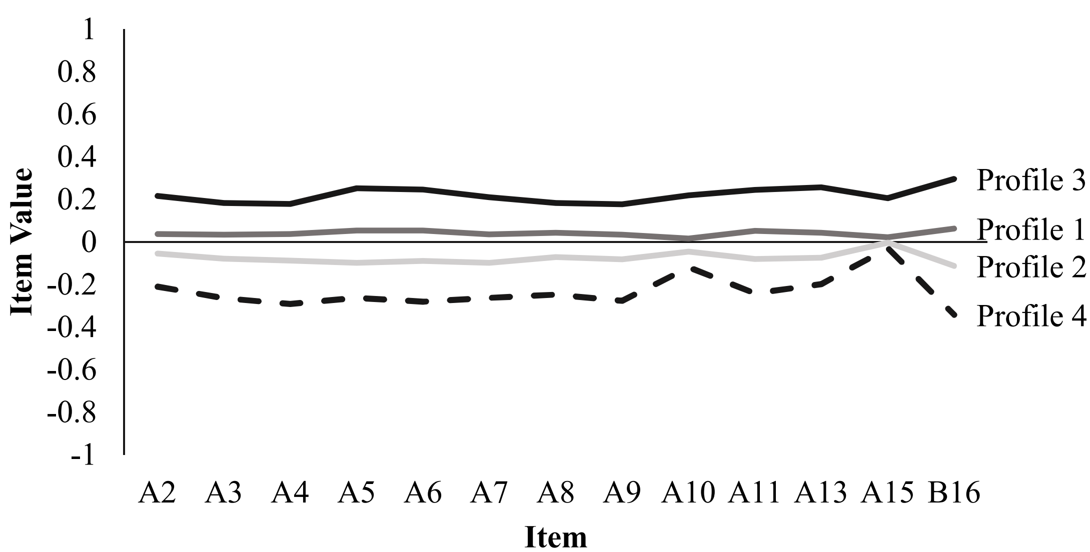

Figure L.5 *Learning environment domain, four-profile upper-level model*

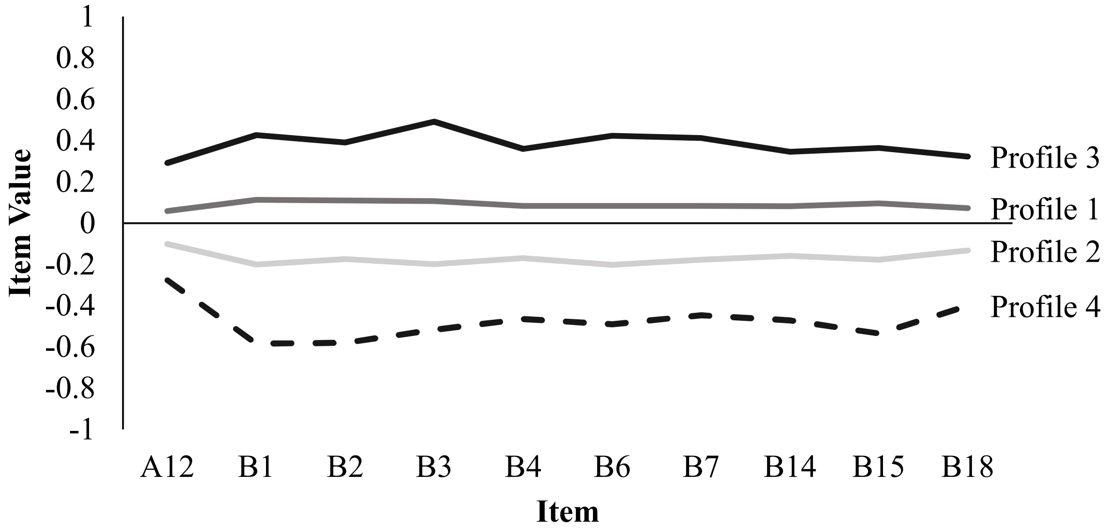

Figure L.6 *Social/physical environment domain, four-profile upper-level model*

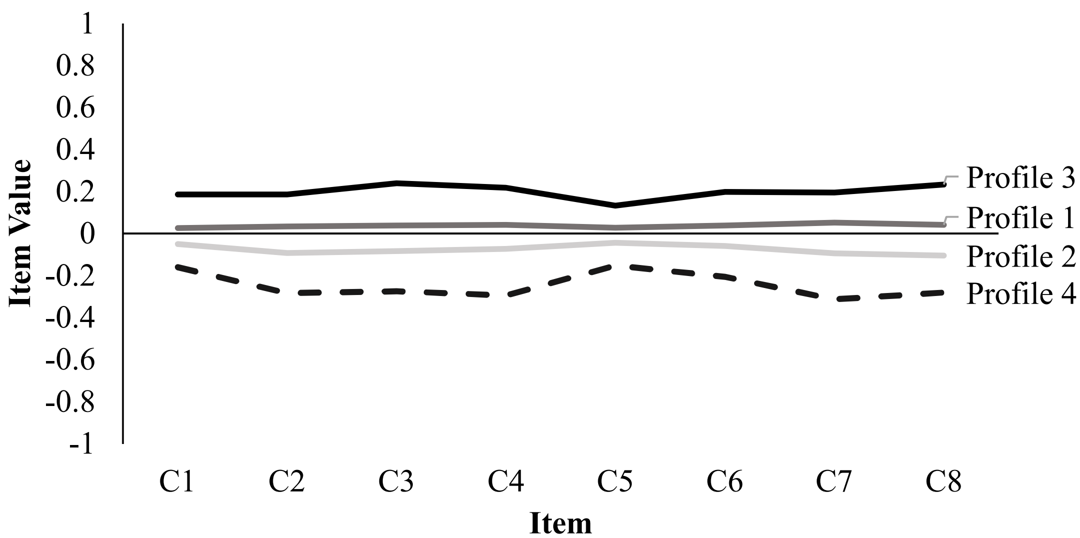

Figure L.7 *Home-school relationship domain, four-profile upper-level model*

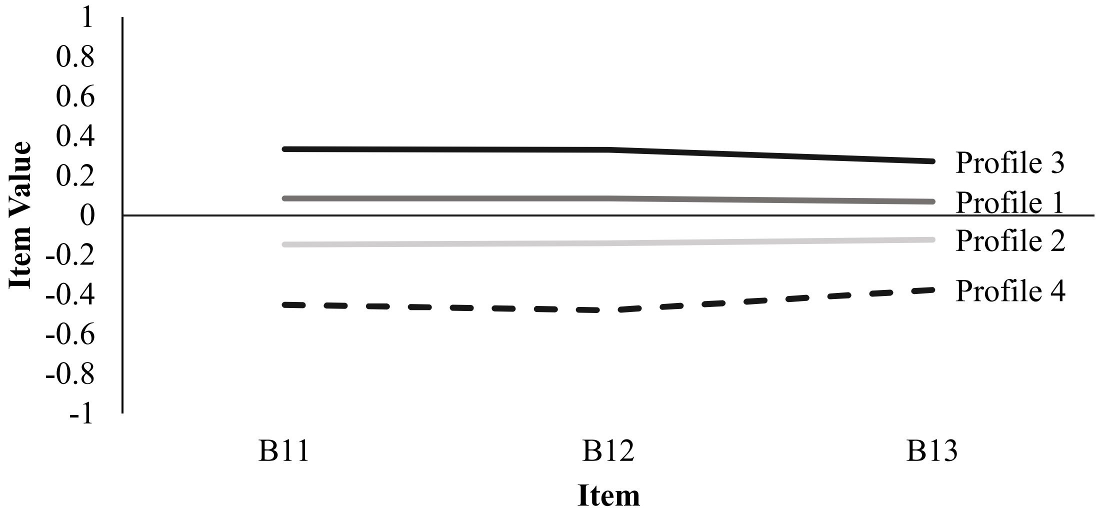

Figure L.8 *Safety domain, four-profile upper-level model*