

# Analyzing Profiles and Predictors of Students' Social-Ecological Engagement

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*Using data from the Educational Longitudinal Study (2002), this study employed latent class analysis (LCA) to explore the relationship between students' engagement-related dispositions and their behavioral engagement in home, school, and community activities. The primary aim was to identify and describe the engagement characteristics of distinct subpopulations of students. Our higher-order LCA models yielded five subpopulation profiles of students' social-ecological engagement. In contrast to extant participation-identification models, these new profiles suggested that the relationship between students' behavioral engagement and their school-related identities and dispositions is nonlinear and nonhomogeneous. This major finding recommends comprehensive school–community improvement models as well as nuanced interventions that are tailor-made to fit the engagement needs and identity-related characteristics of each student subpopulation.*

**Keywords:** *student engagement, school engagement, student motivation, student engagement profiles, student engagement dispositions, extra-curricular activities, latent class analysis*

RESEARCHERS and practitioners agree that student engagement is essential for academic learning and school success (Christenson, Reschly, & Wiley, 2012). Students who are engaged in school tend to have better grades, higher achievement scores, and enhanced chances of postsecondary enrollment and completion (Reschly & Christenson, 2012). Conversely, students who are not engaged in school are more likely to drop out, experience social and academic problems, and have their educational careers end following high school (Rumberger & Rotermund, 2012).

Although the connection between student engagement and positive educational outcomes is well known, finding ways to improve the engagement of high school students remains a work in progress. For instance, in the United States, an estimated 7,000 students drop out of school each day (National Assessment of Educational Progress, 2009). In the same vein, the probability of graduating from high school in some of the poorest urban school districts in the United States is a coin toss (Balfanz & Byrnes, 2012). What is more, when researchers have analyzed students' long-term engagement trajectories, a persistent pattern has emerged. Overall, student engagement tends to decline from elementary school to high school (National Research Council & Institute of Medicine, 2004).

As the search continues for more effective ways to engage high school students at school and in the classroom

(e.g., Cooper, 2014; Turner, Christensen, Kacker-Cam, Trucano, & Fulmer, 2014), some scholars have widened the lens of their research to include analyses of their engagement during out-of-school time (e.g., Lauer et al., 2006). The idea has been that by studying how engagement “works” during nonschool hours, researchers might come to better understand the conditions that facilitate engagement in classrooms and school overall.

One promising line of this research focuses on high school students and their engagement in school- and community-based extracurricular activities (ECAs). This line of research is promising because the majority of today's high school students report active engagement in some kind of (after-school) ECA either at school or in the community (Feldman & Matjasko, 2005).

ECAs often attract the engagement of high school students because they provide them with opportunities to develop skills, interests, and social contacts in settings that are often less restrictive than formal classrooms (Larson, 2000). For this reason, some scholars have suggested that ECAs represent important contexts for positive youth development (e.g., Forneris, Camire, & Williamson, 2014). This potential for positive youth development is the most pronounced when ECAs help students develop new skills and competencies, explore their emergent ideas and interests,



and forge important social ties with peers and positive adult role models (Lerner et al., 2005).

Beyond their immediate appeal, research indicates that ECA engagement correlates with other important benefits for high school students and the schools they attend. One of these benefits is enhanced student engagement in academic work (Feldman & Matjasko, 2005). Here, research indicates that when ECAs help students develop engagement-relevant skills, such as planning, goal setting, and initiative taking, students may employ those skills to complete their academic work, graduate from high school on time, and successfully pursue postsecondary educational careers (Larson, 2000).

Given the importance attached to student engagement in the current Race to the Top educational policy environment (e.g., M. Lawson & Lawson, 2013), these findings hold special significance. Where research is concerned, they highlight needs for studies that provide theoretical and practical insight into a process that might be called “skill and competency transfer” (e.g., Lave, 1997). Where practice and policy are concerned, they invite data-driven models of engagement that can help educators facilitate this transfer across a broader cross-section of students and schools.

The present study was designed with these needs in mind. The goal was to explore subpopulation differences in how high school students transfer their engagement-related skills and competencies across different activities (e.g., ECAs and academics) and social-ecological contexts (i.e., home, school, and community). In pursuit of this goal, we drew a nationally representative sample of 10th-grade public high school students who participated in the Educational Longitudinal Survey of 2002 (ELS). We then used a particular type of statistical technique called latent class analysis (LCA) to explore a novel conceptual-analytic model for student engagement research. This model depicts student engagement as the intersection between students’ *behavioral engagement* patterns at home, school, and the community and their thoughts, feelings, and identity beliefs about school (i.e., their engagement dispositions).

In this study, students’ behavioral engagement patterns were analyzed using multiple measures of student experience, such as their school- and community-based ECA engagement, their school conduct patterns (i.e., attendance, suspensions, and class-cutting behaviors), and their home engagement preferences (e.g., their television-watching and homework patterns). Students’ *engagement dispositions* were modeled using measures of students’ academic motivations and competency beliefs, their affective school attachments, and their aspirations for the future (M. Lawson & Masyn, 2015). LCA was employed to analyze relations among these diverse constructs and indicators and to classify students’ engagement experiences into identifiable subpopulation profiles.

The result of these analyses is a social-ecological view of student engagement. New in one respect, this conceptualization

closely mirrors Bronfenbrenner’s (1979) classic ecological systems theory and today’s social-ecological theory (e.g., Fleury & Lee, 2006). It is noteworthy that this view takes researchers, practitioners, and policymakers outside the school to examine how student engagement in external social settings might relate to their engagement in schools and classrooms. For this reason, results from this study are especially relevant for researchers interested in the social ecology of student learning, engagement, and motivation (e.g., Eccles & Roeser, 2011). They are also important for educational leaders and policymakers interested in school improvement models that provide a more expansive, engagement-focused reach into students’ peer, family, and community ecologies (e.g., Walsh et al., 2014).

The ensuing analysis provides the relevant details. We begin by briefly summarizing research that examines student engagement in particular contexts and settings. We then build from these setting-specific works by highlighting studies that offer a more expansive, social-ecological view of student engagement and its attendant processes. Following a discussion of our conceptual-analytic framework, we present our LCA-derived subpopulation profiles of students’ social-ecological engagement. We conclude by offering select implications for enhanced, engagement-focused educational policies and practices.

## Literature Review and Conceptual Framework

### *Academic and School Engagement Research*

Much of the extant literature has framed engagement as a meta-construct consisting of emotional, cognitive, and behavioral elements (e.g., Fredricks, Blumenfeld, & Paris, 2004). Most of these studies have examined students’ engagement experiences in classroom settings, that is, their *academic engagement* (Skinner & Pitzer, 2012). In these studies, *emotional engagement* typically refers to students’ feelings of identification and belonging to school as well as the level of interest, enjoyment, happiness, boredom, and/or anxiety they experience conducting academic work (e.g., Appleton, Christenson, & Furlong, 2008; Pekrun & Linnenbrink-Garcia, 2012). *Cognitive engagement* refers to students’ psychological investments in learning tasks (Fredricks et al., 2004), the cognitive effort students exert while studying (Finn & Zimmer, 2012), and the extent to which they persist when academic work becomes difficult (Corno, 1993).

Research on students’ behavioral engagement typically draws on the notion of participation (Fredricks et al., 2004). Some of these studies examine students’ prosocial conduct, such as the amount of time students spend on homework (Finn & Volkl, 1993) and/or the extent to which they comply with school rules (Finn, Folger, & Cox, 1991). Other studies, particularly those in the dropout literature, employ these measures as proxies for *student disengagement* and disaffection (Skinner & Pitzer, 2012). Here, researchers have found that

increases in student absenteeism, class cutting, and suspensions represent key contributing factors for ongoing school difficulty and dropout (Rumberger & Rotermund, 2012).

While students' academic engagement in classrooms represents the primary unit of analysis for engagement research, some studies have proceeded with a broader view of students' behavioral engagement experiences. Here, researchers have employed the concept of *school engagement* as they have examined participation in school-based ECAs, such as interscholastic athletics, student government, school-based music and arts programs, and/or school clubs (e.g., Bohnert, Fredricks, & Randall, 2010).

Overall, researchers have found that students' school engagement supports important educational outcomes, such as higher grades (Eccles & Barber, 1999) and higher chances of completing high school (Mahoney & Cairns, 1997). Increases in school engagement have also been shown to reduce the prevalence of problem behaviors, such as school suspensions and juvenile delinquency (Bohnert et al., 2010).

#### *Youth Development and Leisure Studies Research*

A related category of behavioral engagement research is interdisciplinary. It is located in the youth development and leisure studies literatures. This research emphasizes students' out-of-school time (OST) and especially family and community settings for youth development. We use the compound term *home-community engagement* to describe this category of research, with the reminder that it includes a broad range of home- and/or community-based activities.

In this study, two specific types of home-community engagement activities are of particular interest. The first type involves student engagement in *relaxed leisure* activities, like watching television, playing video games, listening to music, and hanging out with friends. These activities are typically described by researchers as "relaxed" because they are unstructured and do not require much cognitive or psychological effort from students (Eccles & Barber, 1999). This lack of structure has been cited as a key reason why relaxed leisure activities are generally not associated with positive educational or developmental outcomes (Feldman & Matjasko, 2005).

The second type of home-community engagement activity examined by researchers involves *constructive leisure* activities in the community, such as participating in organized clubs, faith-based groups, sports teams, and civic engagement activities (e.g., Voight & Torney-Purta, 2013). These activities are typically described as "constructive" by researchers because they require students to develop and practice new skills and competencies in settings that are often structured and supervised by adults (e.g., Forneris, Camire, & Williamson, 2014). Perhaps for this reason, research has associated engagement in constructive leisure activities with a host of positive developmental outcomes

(Eccles, Barber, Stone, & Hunt, 2003; Larson, 2000). Examples of the outcomes associated with these activities include (a) enhanced student perceptions of their academic and social competence, (b) enhanced student connections to positive role models and peer groups, (c) enhanced caring and compassion toward others, and (d) enhanced student contribution to the welfare of their schools, peers, families, and communities (Lerner et al., 2005).

Although research has not fully articulated the mechanisms that link constructive leisure activities to positive social and educational outcomes, scholars have identified three primary variables that, when properly manipulated, can enhance this important relationship (after Bohnert et al., 2010; Gardner, Roth, & Brooks-Gunn, 2008). These variables are the number of times per week students engage in particular activities (i.e., the *frequency* of their engagement), the average amount of time they spend at each activity sitting (i.e., the *intensity* of their engagement), and the number of activities (or activity contexts) they are engaged in at particular points in time (i.e., the *breadth* of their engagement).

#### *Toward a More Expansive Conceptual Engagement Framework*

The preceding review highlights the prized role of engagement as a metaconstruct consisting of affective, cognitive, and behavioral elements. Most of this research has analyzed these elements in classrooms, that is, their *academic engagement*. However, some behavioral engagement researchers have extended the study of engagement to include a broader range of activities and settings. Research that focuses on students' school-based ECA experiences can be classified as *school engagement*. Studies that focus on student experiences in constructive and relaxed leisure activities outside of school can be labeled *home-community engagement*.

Notwithstanding the important strengths of these setting specific works, our review of the literature reveals two important research needs and opportunities. The first need is to better integrate engagement's affective, cognitive, and behavioral elements into single research studies. This need is evident because most studies include only one element of engagement in their research designs (Christensen et al., 2012; Fredricks et al., 2004). Studies that examine two or more remain unusual (for exceptions, see Wang & Eccles, 2012; Wang & Peck, 2013).

The second need is to better understand the relationship between students' academic, school, and home-community engagement experiences. This need is evident because students' experiences at school, home, and community span their entire social lifeworlds. Consequently, in order for engagement researchers to better attend to the engagement-related strengths, needs, and challenges of the "whole child," social-ecological studies of engagement are needed

(Eccles & Wang, 2012; M. Lawson & Lawson, 2013). In the following sections, we provide the conceptual foundations for one such social-ecological engagement model. This model was derived from four important lines of engagement research.

### *Engagement as Participation and Identification*

The first line of research that informed this study's conceptualization is Jeremy Finn's (1989) *participation-identification* model. In this model, *student participation* is operationalized as students' school conduct and classroom compliance, their initiative taking, their ECA engagement, and their participation leadership activities at the school (Finn et al., 1991). Students' *school identification* is an affective variable that is measured along two dimensions: (a) students' perceptions of *school belonging* and (2) students' *affective valuing* of school (e.g., Finn & Zimmer, 2012; Voelkl, 2012).

In Finn's (1989) work, student participation and identification are depicted as continuous variables that operate in synergy, which is to say that they are expected to increase or decrease in tandem. For example, the more students participate in school, the more they are expected to positively identify with school norms and activities and vice versa.

In contrast, students who do not participate in school activities are expected to develop weaker school attachments and comparatively more limited affiliations with prosocial peers. Over time, these undesirable dynamics have been shown to limit students' academic performance and eventually reduce their chances of completing high school (see also Ream & Rumberger, 2008).

### *Engagement and Students' Identity Development*

While Finn's (1989) participation-identification model depicts engagement as a set of interrelated, continuous measures or variables, some leisure studies scholars have conceptualized engagement as a set of categorical constructs (e.g., Bartko & Eccles, 2003). This categorical view of engagement follows research that suggests that students often interpret their social worlds differently, even when they engage in similar activities, contexts, and settings (e.g., Martin et al., 2015). This important and consistent research finding has contributed to a second line of engagement research, one that focuses on the relationship between students' school engagement practices and their developing social identities.

The relationship between students' school engagement and identity beliefs is perhaps best exemplified in Eccles and Barber's (1999) now-classic "Breakfast Club" study. In this study, Eccles and Barber began by surveying students about their school-based ECA engagement. They then supplemented these analyses by analyzing the relationship between students' ECA engagement and their identity constructions.

Eccles and Barber (1999) drew characters from the popular 1980s movie *The Breakfast Club* when they asked students to classify themselves as a "jock," "princess," "brain," "basket case," or "criminal." When these character-driven identities were matched with students' school engagement profiles, Eccles and Barber found that (a) the princesses and jocks were disproportionately engaged in school-based ECAs, (b) the brains were disproportionately engaged in volunteering and faith-based activities, and (c) students who characterized themselves as criminals generally reported low involvement in all manner of school-based ECAs. These findings led Eccles and Barber to conclude that students' "school-based activity identities" represent a critical mechanism for helping students engage in school and pursue post-secondary educational careers (see also Eckert, 1989).

### *Person-Centered Engagement Research*

A third important line of engagement research takes a broader, "person-centered" view of students' behavioral engagement. These studies are often described as person centered because they provide an especially holistic view of how student engagement "works" across a diverse array of activities (e.g., ECA engagement, household chores, and work) and social contexts (i.e., home, school, and community).

To facilitate this holistic view, some engagement scholars have analyzed their engagement variables using a particular type of person-centered statistical technique called cluster analysis (e.g., Linver, Roth, & Brooks-Gunn, 2009; Peck, Roeser, Zarrett, & Eccles, 2008). Cluster analysis has been a preferred analytical tool for these engagement researchers because it enables them to identify students who share similar school, home, and community engagement patterns. Researchers then use these engagement patterns or "clusters" to classify students' behavioral engagement experiences into identifiable subpopulation profile groups (Roeser & Peck, 2003).

For example, Peck et al. (2008) used cluster analysis to model the behavioral engagement profiles of 1,350 African American and White students who participated in the Maryland Adolescent Development in Context study. Their analyses yielded nine distinct profiles of student engagement behaviors at home, school, and the community. Of these profiles, five included engagement in school-based sports activity, another involved student participation (volunteering and work) in the community but not at school, and another involved engagement in ECAs at school that did not include sports. Their final behavioral engagement cluster was characterized by students who largely stayed at home, read, and watched large amounts of television.

Using a comparable design, Linver et al. (2009) conducted cluster analyses on a nationally representative sample of about 1,700 students ages 10 to 18 from the Child Development Supplement of the Panel Study of Income Dynamics. Their analysis revealed five distinct clusters of

behavioral engagement. These five clusters were (a) a “sports” cluster, which was characterized by high sports participation and lower participation in other activities; (b) a “sports plus” cluster, populated by students who participated in multiple activities including sports; (c) a “school groups” cluster, characterized by high rates of participation in school activities and lower participation in other activities; (d) a “religious groups” cluster, whose members participated in faith-based youth groups; and (e) a “low-involved” cluster, whose members manifested low mean levels of participation across all measured activities.

Significantly, additional regression analyses indicated that these behavioral engagement clusters were predictive of variations in students’ connectedness with school (i.e., their emotional engagement). For example, Linver et al. (2009) found that students involved in sports plus other ECAs had school connectedness scores that were nearly half of a standard deviation higher than students who participated in sports alone. They also found that students who were involved exclusively in sports had significantly higher school connectedness scores than students who were not involved in school-based ECAs.

#### *Social-Ecological Engagement Research*

A final line of engagement research follows M. Lawson and Lawson’s (2013) recent review of extant engagement research and theory, with particular interest in the social-ecological model of engagement they recommended. This model emphasizes relations between two primary engagement components: (a) students’ *behavioral engagement* patterns at home, school, and the community and (b) students’ thoughts, feelings, attitudes, and identity beliefs about school (their *engagement dispositions*). This dual focus on behavioral engagement and engagement dispositions derives from Finn’s (1989) foundational research.

M. Lawson and Lawson’s (2013) broad conceptualization of behavioral engagement included relevant indicators of students’ school, academic, and home-community experiences, and it followed these researchers’ argument that engagement research, policy, and practice needed to become more nuanced and less formulaic. Such a nuanced approach was grounded in twin ideas: (a) Students’ behavioral engagement “works” differently across the social settings for engagement, and (b) in lieu of research focused on a general categorization of “the students,” researchers need to look for situational uniqueness and subpopulation difference. Consistent with these ideas, M. Lawson and Lawson recommended that researchers examine students’ behavioral engagement patterns using person-centered research designs (e.g., Peck et al., 2008).

The second component in M. Lawson and Lawson’s (2013) engagement model is the nascent and perhaps controversial concept of a student engagement disposition (see also Crick, 2012; Crick & Goldspink, 2014; M. Lawson &

Masyn, 2015). This disposition construct is derived from Finn’s (1989) work on school identification as well as scholarship that links student engagement to students’ school-based identity constructions (e.g., Eccles & Barber, 1999; Eccles & Roeser, 2011).

As articulated by M. Lawson and Lawson (2013), an engagement disposition develops from interactions between students’ thoughts and feelings about school, their behaviors, and the quality and characteristics of their social environment (see also M. Lawson & Masyn, 2015).

Like the school identification concept (Finn, 1989), an engagement disposition has an affective dimension indicated by students’ school valuing and affective belonging (e.g., Voelkl, 2012). In addition, an engagement disposition includes a cognitive dimension. This cognitive dimension reflects students’ perceptions of “will” and the “skill” they bring to academic learning as well as to the school overall. Together, these two dimensions frame an engagement disposition as a particular kind of school-related identity, one that reflects students’ thoughts and feelings about who they are in school, who they have been, and who they want to become (see also Goldin, Epstein, Shorr, & Warner, 2011; Oyersman, Johnson, & James, 2011).

A final difference between Finn’s (1989) pioneering work and the M. Lawson and Lawson (2013) social-ecological model extends to differences in how their respective primary variables are treated analytically in research designs. These differences are consequential for student engagement research, theory, and practice because they provide researchers, educators, and policymakers with qualitatively different views of the participation-identification relationship. For example, in Finn’s research, student participation and identification are operationalized as continuous variables that are expected to enjoy a linear, synergistic relationship. In contrast, in M. Lawson and Lawson’s model, students’ engagement behaviors and dispositions are conceptualized as categorical constructs whose relationship may not follow a simple line of linear prediction.

Thus, while Finn’s (1989) work facilitates a synergistic view participation-identification relationship, M. Lawson and Lawson’s (2013) model provides researchers with fresh opportunities to explore those factors that might lead some students to participate in but not identify with school as well as those that might lead others to identify with school but not participate. Accordingly, this study was designed to capture the nuance of the participation-identification relationship by way of a person-centered, social-ecological model for student engagement research.

#### *An Emergent Typology of Student Engagement Dispositions*

In a previous study, the authors made progress in modeling M. Lawson and Lawson’s (2013) two-component engagement model. This effort began by using a unique kind of person-centered statistical method called LCA to identify

different subpopulation profiles of student engagement dispositions. This LCA approach was applied to data drawn from a nationally representative sample of public high school students who participated in the ELS.

In the above-mentioned study, a student engagement disposition was formulated as a categorical concept defined by a discrete typology of student identification (and dis-identification) toward academics and school overall. Guided by M. Lawson and Lawson's (2013) theoretical framework, these different types (or profiles) of student engagement dispositions were modeled using those ELS survey items that we believed best characterized students' thoughts, feelings, attitudes, and identity beliefs toward school. As detailed in Appendix A, these ELS survey items measured students' interest and enjoyment toward academics, their affective school attachments, and their educational and occupational aspirations. Moreover, because interest resided in understanding how students might engage or identify with some aspects of schooling but not others, our LCA models included several indicators of students' student ambivalence (Priester & Petty, 1996) and dis-identification (Steele, 1997) toward school.

Our LCA of these indicators yielded six characteristically distinct profiles of student engagement dispositions. To assist reader interpretation of these profiles, a graphic depiction of each student engagement disposition is provided in Figure 1. A brief summary of each profile follows.

The first disposition profile yielded from the M. Lawson and Masyn (2015) study was the *academic initiative* class. Students belonging to the academic initiative class generally enjoyed both math and reading, and they approached their academic work with senses of efficacy, effort, and persistence. The second disposition profile was the *academic investment* class. In contrast to the more intrinsic forms of academic engagement exhibited by the academic initiative class, academically invested students appeared to engage in school not because they enjoyed it but because they perceived it would yield future educational benefits and occupational rewards.

The third disposition profile was the *low-effort/efficacy* class. Students in this profile generally did not feel efficacious about their academic work, nor did they put forth their best effort when studying. They also generally did not persist when academic work became difficult. They did, however, believe that they would attend and complete a 4-year college or university.

The fourth disposition profile was the *boredom* class. Consistent with this moniker, students in this profile did not find school interesting, challenging, or enjoyable even though they generally viewed themselves as efficacious in school. The fifth disposition profile was the *ambivalence* class. These students were characterized as ambivalent because they appeared generally unsure about their prospects for educational and/or occupational success. For

example, fewer than half of these students believed that they would graduate from a 4-year college or university, and only 50% thought it was important to be successful in their future line of work.

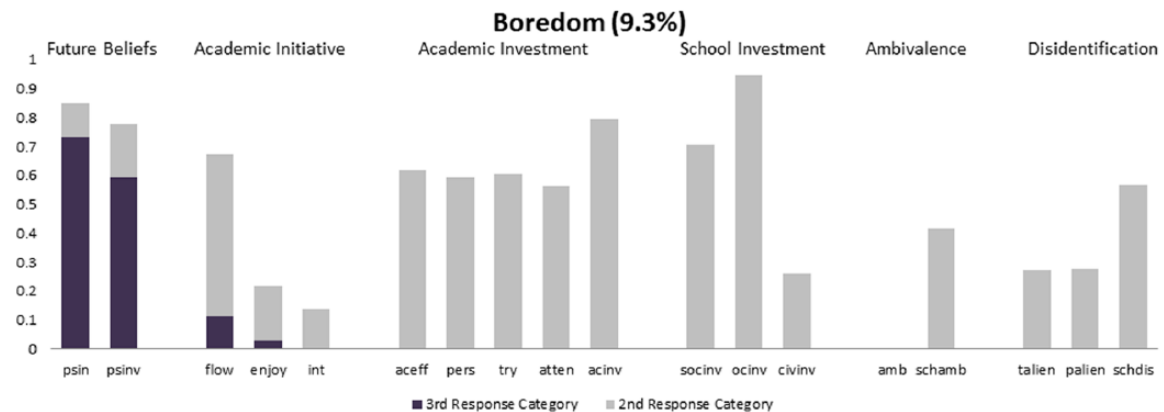
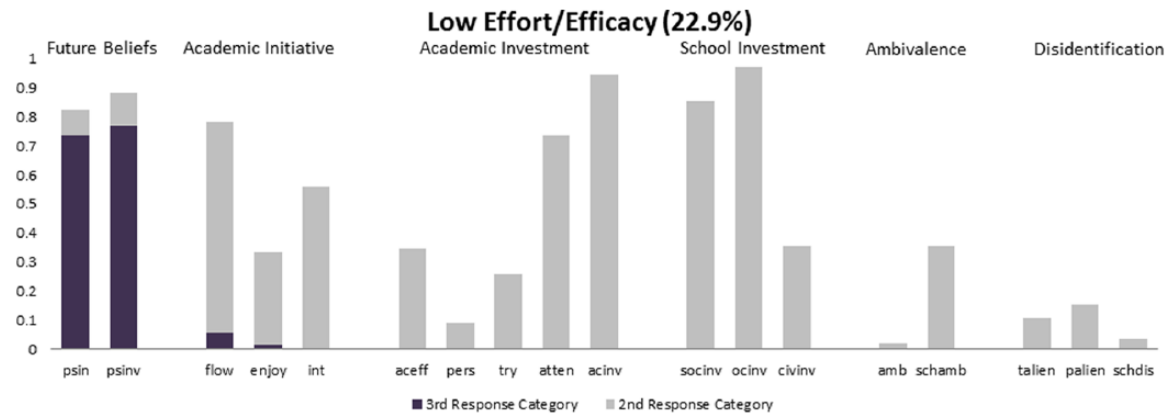
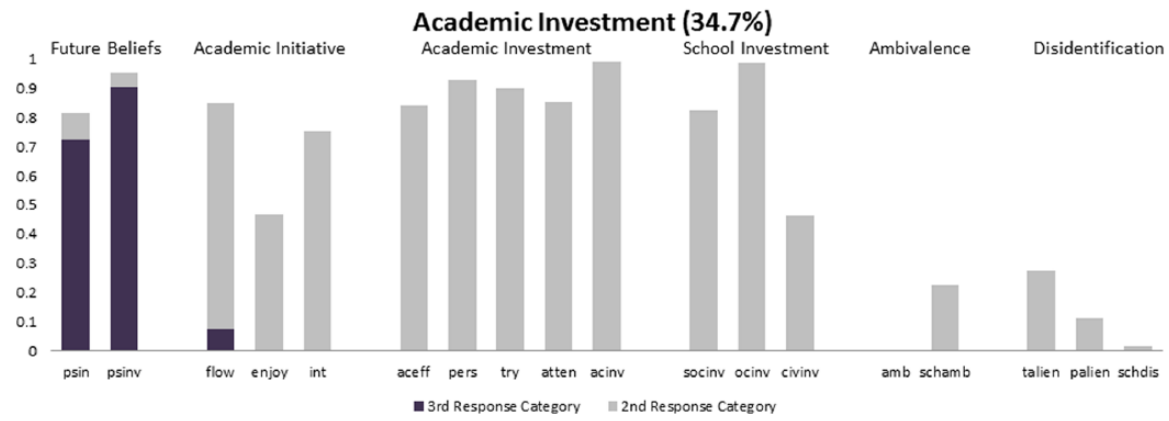
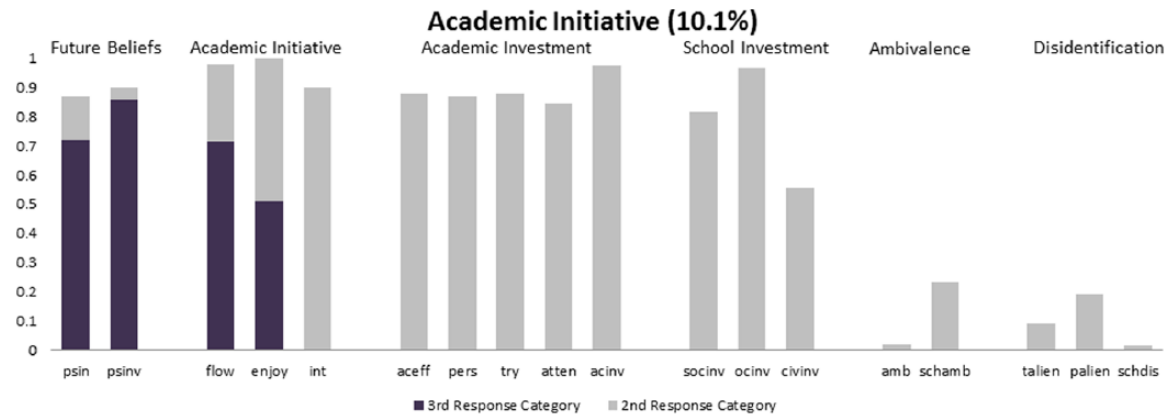
The sixth and final disposition profile was the *dis-identification* class. Students in the dis-identification profile appeared cognitively and affectively detached from their current or future educational pursuits. For instance, they were unlikely to find academic work interesting, challenging, or enjoyable, and they did not think that getting good grades was important. They also had less than a 50% chance of perceiving that their educational careers would advance beyond high school.

### The Present Study

The present study examines a novel social-ecological model for student engagement research. This conceptualization depicts student engagement as the intersection between students' behavioral engagement in academic, school, and home-community settings and their respective dispositions toward school and schooling. Because interest resided in exploring multiple aspects of this engagement model and framework, the analyses were organized to attend to three complementary research objectives.

The first research objective was to analyze the behavioral engagement component of M. Lawson and Lawson's (2013) social-ecological model. Guided by our review of relevant research, we used LCA to analyze 15 different indicators of students' behavioral engagement at school, home, and the community. These indicators included measures of engagement in "constructive leisure" activities, like school-based and community-based ECAs, as well as measures of "relaxed leisure" activities at home, such as watching television and playing video games. Moreover, because we were interested in understanding how students might engage with—or dis-engage from—some activities/settings and not others, we analyzed measures of student attendance, class cutting, and suspensions as indicators of students' behavioral engagement (see also Wang & Peck, 2013) rather than an outcome or consequence of it (e.g., Eccles & Barber, 1999).

The second research objective of this study was to advance a data-driven view of engagement that could inform the development of more responsive, engagement-focused teaching and learning practices. To assist in the development of these models, we used latent class regression analysis to estimate associations between a vector of student background factors (e.g., student socioeconomic status [SES], ethnicity, and ninth-grade grade point average [GPA]) and students' behavioral profile membership. The main idea here was to help educators, school leaders, youth development specialists, and policymakers understand the social-demographic characteristics associated with each behavioral engagement profile group.



(continued)

FIGURE 1. (continued)

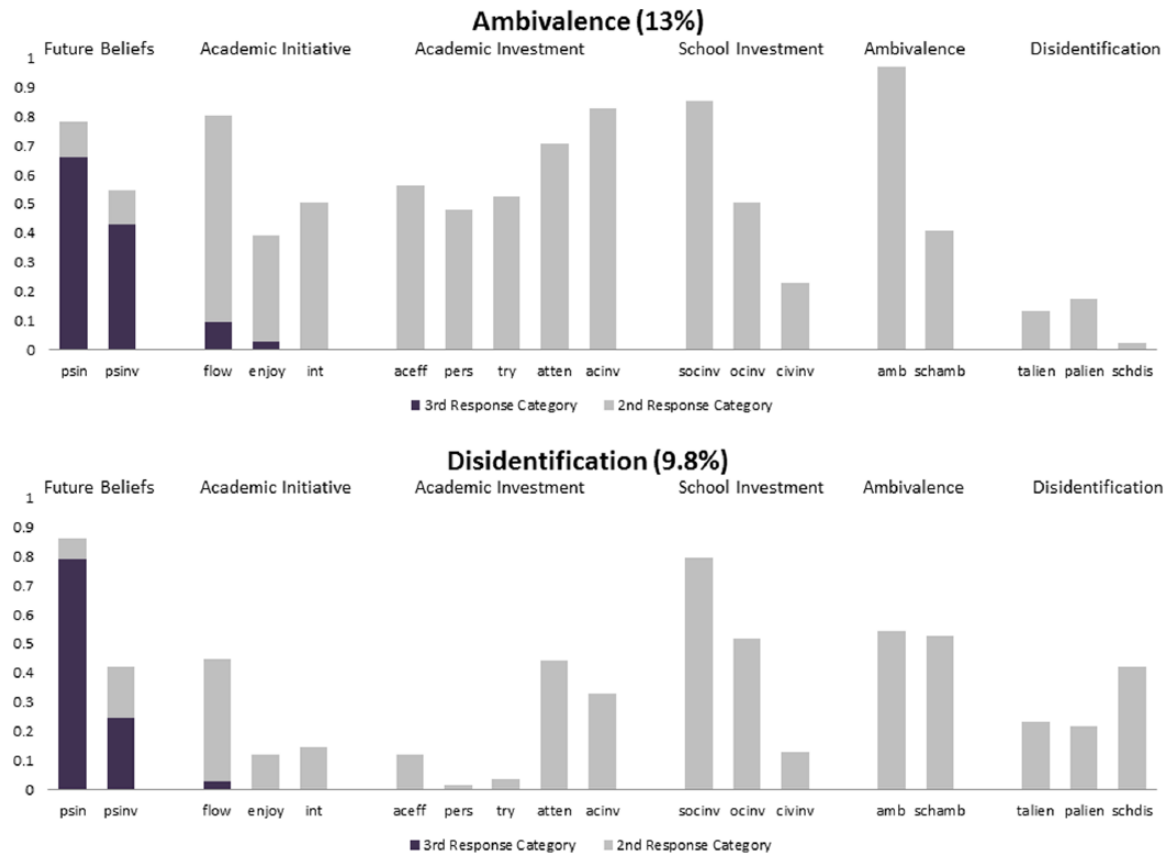


FIGURE 1. Profiles of student engagement dispositions.

Our third and final research objective was to analyze relations between the two primary engagement components depicted in M. Lawson and Lawson’s (2013) social-ecological model. To accomplish this objective, we used LCA to model relationships between the behavioral engagement profiles yielded from this present study and the six profiles of student engagement dispositions identified from previous work (i.e., M. Lawson & Masyn, 2015). These analyses yielded the social-ecological profiles of student engagement that represent this study’s primary theoretical and practical contribution to the research literature.

**Method**

*Data Source and Sample*

Participants in this study were recruited into the ELS. The ELS is a nationally representative cohort study sponsored by the National Center for Educational Statistics (2004). It includes multiple waves of student data starting in the base year of 2002, when students were high school sophomores, and concluding in 2012, when students were 6 years out of high school.

In the present study, we analyzed restricted data from the first two waves of the ELS data set. Data from the first or “base year” ELS data file were used to estimate our behavioral engagement and engagement disposition profile models. Data collected from the first ELS follow-up study of 2004 (when most of these students were high school seniors) were used to analyze predictors of student membership in each behavioral profile group.

Consistent with our previous analysis on students’ engagement dispositions (M. Lawson & Masyn, 2015), the sample for the present study was delimited to 10th-grade students attending public high schools in the United States who also had follow-up data in 2004. Because the LCA approach employed in this study allows for missing data on measured indicators (no students had missing data on all measured LCA indicators), our LCA models were based on results culled from a sample of 12,760 tenth-grade students attending nearly 600 different public high schools in the United States.<sup>1</sup>

*Measures*

A total of 15 binary and ordinal variables, based on responses to single or multiple items from the ELS survey,

were used as observed indicators of the latent typology of students' behavioral engagement, specified in this study as a categorical latent class variable. Informed by our literature review, these variables—which are referred to as “manifest variables” in LCA—were organized into three conceptual groups. The first conceptual group consists of items that measured student engagement in school-sponsored ECAs, including school sports, school arts, school service, and community service. The second category of manifest variables includes measures of the intensity of students' behavioral engagement in constructive and relaxed leisure activities at school, home, and the community. The third category of manifest variables, indicators of student conduct, includes ELS items that measured student attendance, suspensions, and class-cutting behaviors. A complete account of these variables can be located in Appendix B. A brief summary of each follows.

*Indicators of Engagement in School-Sponsored ECAs.* Seven manifest variables were used as indicators of students' behavioral engagement in school-sponsored ECAs. These ECA variables were coded as dichotomous items because the activity questions in the ELS survey did not allow us to capture the number of ECAs students were engaged in at particular points in time. In light of this limitation, we followed the recommendation of Bohnert et al. (2010) and created dichotomous variables for each school-based ECA. This strategy was employed so that we could model the breadth of students' school engagement experiences (e.g., sports, arts, and service). Each of these variables was coded 1 if students reported that they were engaged in that particular type of school-sponsored ECA and 0 if they did not.

The first such indicator of school-based ECA breadth was structured interscholastic sports (“sports”). This variable measured whether students engaged in individual or team sports at the school. The second sports-related variable, unstructured school sports (“intramural”), measured whether students were engaged in intramural sports activities at the school. The third variable, school arts (“arts”), measured whether students were engaged in school band, chorus, or a play/musical.

The next four ECA variables were coded to capture student engagement in school-sponsored clubs and related service activities. The first of these variables, school service (“service”) measured whether students were engaged in one or more of the following activities at the school: student government, school yearbook or newspaper, school service clubs, and/or school hobby clubs. The vocational club (“voclub”) variable measured whether students engaged in at least one vocational development opportunities at school, such as job shadowing or professional internships. The academic club (“saclub”) variable measured whether students engaged in at least one academic club at the school, including activities such as participating in the National Honor Society. Finally, the community service (“comserve”) variable

measured whether students engaged in school-sponsored civic engagement and service activities in the community.

*Indicators of Activity Intensity.* Activity intensity refers to the amount of time students devoted to engaging in constructive or relaxed leisure activities during the day or week (Bohnert et al., 2010). Five ordinal variables were utilized to measure the intensity of students' behavioral engagement in these kinds of activities. The first of these variables captured the intensity of students' behavioral engagement in school-sponsored ECAs (“ecin”). This ordinal manifest variable was coded 2 if students engaged in school-sponsored ECAs for more than 2 hours a day during the week, 1 if they engaged for 2 or fewer hours a day, and 0 if they reported that they did not participate in school-sponsored ECAs.

The second intensity indicator measured the amount of time students engaged in community-based ECAs (“ost\_in”), such as taking language or music classes or engaging in community-based sports teams. Similar to the other remaining indicators of activity intensity, this variable was worded in ELS in a way that captured not only the intensity of student's community-based ECA engagement but also the extent to which students engaged in these activities at all. For this reason, this ordinal variable was coded 2 if students reported that they engaged in structured community-based constructive leisure activities two or more times per week, 1 if they engaged less than two times per week in OST activity, and 0 if they did not participate at all in structured OST activities.

The third indicator of activity intensity measured the amount of time students spent engaging in relaxed leisure activities during the weekday. For this study, student engagement in relaxed leisure activity was operationalized as the amount of time students spent watching television and playing video games during the weekday (“tv\_vid”). This ordinal variable was coded 2 if students reported spending 4 or more hours a day watching television or playing video games, 1 if they spent from 1 to 4 hours a day watching television or playing video games, and 0 if they spent less than an hour a day watching television or playing video games during weekdays.

The fourth measure of activity intensity captured student reports of the amount of time they devoted to their homework (“hw”) each school day. This ordinal variable was coded 2 if students devoted more than 2 hours a day to homework, 1 if they worked on their homework for 1 to 2 hours each day, and 0 if they did not do their homework (or if no homework was assigned).

The final indicator of activity intensity measured the amount of time students spent engaging in reading (“read”) that was not assigned by the school. Although this variable was coded in ELS to accommodate multiple hours of reading activity, few students in the ELS data set reported reading materials that were not assigned by the school. As a consequence, in contrast to the other variables, which were

coded to accommodate three response categories, this dichotomous variable was coded 1 if students reported reading for 1 or more hour a day and 0 if they did not.

*Indicators of School Conduct.* Following the work of Wang and Peck (2013), three measures of student conduct were employed to capture students' behavioral engagement and disengagement in academics and school overall. The first such variable, student class cutting ("cut"), was coded 2 if a student reported cutting class three or more times during the first quarter/semester of their sophomore year, 1 if they cut class one or two times, and 0 if they did not engage in class-cutting behaviors.

The second conduct indicator analyzed in this study was student absences ("abs"). In order to avoid mistaking mild illness for disengagement, students who reported being absent from school on two or fewer occasions were coded 0. Students who reported three to six absences during the first few months of school were coded 1, and students who reported seven or more absences during the first semester/quarter of the school year were coded 2.

The third and final indicator of student conduct was student suspensions ("susp"). In this study, student suspensions was a composite variable that includes incidents of both in-school and out-of-school suspensions. This variable was coded 2 if students reported that they were suspended three or more times during the first quarter/semester of the school year, 1 for students who were suspended once or twice, and 0 for students who had not been suspended.

*Predictors of Behavioral Profile Membership.* Four predictor variables were utilized to help identify the social-demographic features of each LCA behavioral profile. The first two variables, students' SES and students' ninth-grade GPA in core academic courses, were scaled in ELS as continuous variables. The second two variables, student race/ethnicity (African American, Hispanic, Asian, Other, or White) and gender (male or female), were recoded into dummy variables. White and female students were entered as the reference group for the ethnicity and gender dummies, respectively.

*Student Engagement Dispositions.* The typology of student engagement disposition was represented as six-category latent class variable based on a previous LCA of the same sampled population (e.g., M. Lawson & Masyn, 2015). These profile classes were labeled (a) academic initiative, (b) academic investment, (c) low-effort/efficacy, (d) boredom, (e) ambivalence, and (f) dis-identification.

### *Analytic Approach*

Our analytic approach was designed to attend to the three primary research objectives that were highlighted at the end of our literature review. In this section, we provide a

conceptual overview of the analytic procedures we used to pursue these objectives. A more detailed, technical account of our analytic procedures can be located in Appendices C, D, and E. All analyses for this study were conducted using the software program Mplus 7.3 (Muthén & Muthén, 2014).

*First-Stage Analytic Approach: Latent Class Enumeration and Split-Half Cross-Validation.* The first objective of this study was to identify different subpopulation profiles of students' behavioral engagement at home, school, and the community. In order to measure students' engagement behaviors in these settings as distinct subpopulation profiles, we utilized a particular form of person-centered statistical modeling called LCA.

LCA can be thought of as a type of stochastic, model-based clustering technique. A population model is specified wherein the overall joint distribution of the observed variables (i.e., the latent class indicators) is assumed to be the result of a mixing of two or more unobserved subpopulations, or latent classes, each with its own unique class-specific distribution of the observed indicators (Masyn, 2013). These class-specific distributions are what characterize the typology of a particular phenomenon of interest. The number and nature of the latent classes is unknown at the onset of the analysis—assumed a priori is that the overall population heterogeneity can be represented by a finite number of homogeneous subpopulations. Latent classes are extracted from the data using statistical and substantive criteria based on model-data consistency, relative fit, and substantive utility, interpretability, and distinctness of the resultant classes, as detailed below.

The first step in conducting LCA is to determine the correct or optimal number of latent classes in the data—a process commonly known as latent class enumeration (Masyn, 2013). The latent class enumeration process begins by estimating a LCA model that has one latent class. From there, researchers add successive latent classes until there are no conceptual or empirical improvements in their models (Nylund, Bellmore, Nishina, & Graham, 2007; Van Horn et al., 2008).

As a general rule, researchers typically evaluate the relative empirical fit of their LCA models by comparing the values of the three primary fit indices. These indices are the Bayesian information criterion (BIC), the consistent Akaike information criterion (CAIC), and the approximate weight of evidence criterion (AWE). In each case, the LCA model that yields the smallest value on a given index is judged as best among the models under consideration (Masyn, 2013).

Beyond the fit indices referenced above, the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) has also been shown to help researchers identify the optimal number of latent classes in their data. For this reason, we used it together with BIC, CAIC, and AWE to guide our latent class enumeration procedure. The LMR-LRT provides a  $p$  value for a  $K$ -class

TABLE 1

*Descriptive Comparison of Calibration and Validation Samples*

Variable	Sample A		Sample B	
	Calibration Sample ( $n = 6,380$ )		Validation Sample ( $n = 6,380$ )	
	$M$	$SE$	$M$	$SE$
Black	0.14	0.01	0.13	0.01
Hispanic	0.15	0.01	0.14	0.01
Asian	0.03	0.01	0.03	0.01
Other	0.05	0.01	0.03	0.01
Male	0.49	0.01	0.49	0.01
Ninth-grade GPA	2.55	0.02	2.56	0.01
Socioeconomic standing	−0.51	0.03	−0.46	0.03
School sports	0.51	0.01	0.51	0.01
Intramural school sports	0.34	0.01	0.36	0.01
School arts	0.23	0.01	0.24	0.01
School service	0.25	0.01	0.25	0.01
School academic club	0.09	0.00	0.09	0.01
School vocational club	0.09	0.00	0.10	0.01
Community service	0.18	0.00	0.19	0.01
School reading <sup>a</sup>	0.23	0.01	0.23	0.01
Homework activity <sup>b</sup>	0.22	0.01	0.22	0.01
School absences <sup>c</sup>	0.49	0.01	0.49	0.01
Class cutting <sup>d</sup>	0.44	0.01	0.45	0.01
School suspension <sup>e</sup>	0.24	0.01	0.24	0.01

Note. SE = linearized standard error; GPA = grade point average.

a. Proportion of students who report more than 2 hours of homework per night.

b. Proportion of students who watch television/video games for 4 or more hours daily.

c. Proportion of students who were absent three or more times during first semester of 10th grade.

d. Proportion of students who cut class at least once during first quarter of 10th grade.

e. Proportion of students who were suspended at least once during first quarter of 10th grade.

model versus a  $(K + 1)$ -class model, with the first nonsignificant  $p$  value indicating a lack of statistically significant improvement in model fit adding another class in the enumeration.

In addition to measures of statistical fit, researchers often evaluate their LCA models by judging the substantive utility of the emergent classes, using two particular statistical parameters of interest: class probabilities and item probabilities. *Class probabilities* represent the relative size of each latent class—for example, the estimated proportion of the student population who belong to each latent class (Masyn, 2013; Nylund, 2007). *Item probabilities* represent the probability of endorsing a particular item conditional on class membership (Masyn, 2013). For example, if class  $k$  had an estimated item endorsement of .85 for participation in interscholastic sports, then a student belonging to class  $k$  would have an estimated probability of .85 of positively endorsing that item. Alternatively stated, 85% of the students in class  $k$  would report participating in interscholastic sports. Thus, the class-specific item probabilities can be used to identify responses

that typify members of a given latent class. They can also be used to distinguish members of one latent class from another.

*Split-half validation.* In addition to the metrics highlighted above, our latent class enumeration process was further guided by a split-half cross-validation procedure. This procedure was conducted to gauge the extent to which our profile findings might replicate to an independent data set. In this procedure, we randomly divided our total sample from the ELS data set into two equally sized split halves (see Table 1; Van Horn et al., 2008). From there, we conducted the above-referenced latent class enumeration procedures on the calibration sample (Sample A), evaluating the BIC, CAIC, AWE, and LMR-LRT. Then, we conducted a smaller set of LCA models on the validation sample (Sample B) using the top-fitting models from Sample A. Ultimately, our final latent class solution was the one that yielded results (i.e., item probabilities and class probabilities) that were the most closely replicated across our calibration and validation samples.

*Second-Stage Analytic Approach: Analyzing Predictors of Students' Behavioral Engagement.* The second objective of this study was to understand the social-demographic features associated with each behavioral engagement profile. In order to analyze these associations, we fit a series of latent class regression models. Following the procedures documented elsewhere (M. Lawson & Masyn, 2015), we conducted these analyses using 10 imputed data sets of covariates and plausible latent class membership that were estimated using the full ELS data set of 12,760 tenth-grade students. In these models, our LCA-derived profiles of students' behavioral engagement were specified as a multinomial outcome variable, while variables such as student SES, ethnicity, gender, and ninth-grade GPA were positioned as predictors of behavioral engagement class membership.

*Evaluating the results and significance of latent class regression models.* One of the challenges of conducting latent class regression analysis stems from the complexity involved in interpreting multinomial logistic regression models. This difficulty is especially pronounced in studies, like this one, where the multinomial outcome variable of interest lacks a conceptually meaningful reference category. In such cases, in order for researchers to explain the meaning and significance of each coefficient yielded from their models, they often have to conduct a series of pairwise tests (e.g., the odds of being in Latent Class 1 versus Class 2 for Black students compared to White students, conditional on membership in Class 1 or 2; the odds of being in Latent Class 1 versus Class 3 for Black students compared to White students, conditional on membership in Class 1 or 3; and so forth). Unfortunately, when the number of multinomial outcomes categories and/or predictors is large, these pairwise analyses can quickly become unwieldy.

Two analytic strategies were employed to address these challenges. First, in order to enhance reader interpretation of our results, we converted the conditional log odds ratios yielded from our latent class regression models into a probability scale. This approach allows readers to compare results between and within outcomes categories using a more user-friendly statistical metric.

Second, in order to evaluate the statistical significance of each multinomial logistic regression coefficient, we conducted a series of "global hypothesis tests." Essentially, each of these global hypothesis tests evaluates simultaneously whether all of the multinomial logistic regression coefficients associated with a particular predictor are equal to zero. This null hypothesis corresponds to "no association" between the predictor and the multinomial outcome, controlling for all other predictors. Thus, a significant  $p$  value translates to statistically significant evidence of an adjusted association between the given predictor and latent class membership.

*Third-Stage Analytic Approach: Analyzing Profiles of Students' "Social-Ecological" Engagement.* The third research objective of this study was to explore how different profiles of students' behavioral engagement related to their engagement dispositions. Using the "three-step" approach to LCA described in Appendix D and elsewhere (e.g., Nylund-Gibson, Grimm, Quirk, & Furlong, 2014), these associations were analyzed in two ways. First, we fit a multinomial logistic regression model where our profiles of student engagement dispositions were specified as a latent multinomial outcome variable with six categories while students' behavioral engagement profiles were specified as a multinomial predictor variable with seven categories.<sup>2</sup> These analyses were conducted to understand the extent to which students' behavioral engagement profiles were distributed across all disposition class groups.

Our second set of relational models analyzed the dominant patterns of student engagement that emerged across all of the latent dispositional and behavioral classes. Here, we used a similar three-step LCA method to specify a higher-order model of student engagement. In this approach, our LCA-derived dispositional and behavioral profile variables served as indicators for a higher-order latent class variable that represented our social-ecological profiles of student engagement. A detailed description of the methods used to estimate these higher order LCA models is provided in Appendix E.

## Results and Discussion

### *Identifying Optimal Class Solutions*

Results of the class enumeration process for students' behavioral engagement profiles are provided in Table 2. The models with more than nine classes were not well identified, meaning that they did not converge or they included one or more latent classes that included less than 1% of the student population (a sign of potential overextraction of classes). Moreover, as shown in the table, the identification of the optimal latent class solution for students' behavioral engagement was not entirely straightforward. Specifically, there was conflicting information across the fit indices. The LMR-LRT indicated no significant improvement in model beyond the six-class solution. The AWE achieved a minimum value at the six-class solution. Last, the BIC and CAIC had the smallest values at the eight-class solution. This ambiguity required us to evaluate the six- through eight-class model solutions with respect to their conceptual merits as much as their empirical fit and replicability across the split halves.

Ultimately, we chose the seven-class solution as the best model for classifying students' behavioral engagement into subpopulation profiles. We chose this model because the eight-class solution did not replicate from the calibration to the validation sample. In addition, the seven-class model included a *disaffected* behavioral profile that mirrored extant

TABLE 2

*Fit Indices for Latent Class Analysis of Students' Behavioral Engagement (Sample A, n = 6,380)*

Model	LL	npar	BIC	CAIC	AWE	Adjusted LMR-LRT $\chi^2$	( $K$ vs. $K + 1$ ) $p$
1 class	–58895	22	117982	118004	118241	5784.43	<.001
2 class	–55896	45	112187	112232	112716.2	5967.17	<.001
3 class	–54925	68	110446	110514	111245.4	1933.18	<.001
4 class	–54255	91	109308	109399	110378.3	1332.42	<.005
5 class	–53875	114	108748	108862	110088.8	757.739	.006
6 class	–53568	137	108337	108474	<b>109947.7</b>	610.031	<b>.06</b>
7 class	–53396	160	108194	108354	110075.4	342.624	.69
8 class	–53275	183	<b>108154</b>	<b>108337</b>	110305.8	240.359	.79
9 class	–53179	206	108162	108368	110584.9	191.919	—
10 class	Not well identified						

*Note.* Boldface type within the table denotes the optimal latent class solution according to each fit index. LL = log likelihood; npar = number of free parameters; BIC = Bayesian information criterion; CAIC = consistent Akaike information criterion (CAIC); AWE = approximate weight of evidence criterion; LMR-LRT = Lo-Mendell-Rubin likelihood ratio test.

research and theory on behavioral disengagement (e.g., Skinner & Pitzer, 2012). The six-class model did not include a disaffected engagement subtype.

#### *Latent Class Behavioral Profile Findings*

For the seven-class model, our split-half cross-validation procedure yielded only slight differences in the corresponding item and class probabilities between our calibration and validation samples. The overall replication of our behavioral profile findings was important because it provided important preliminary support for their measurement validity.

Using the results from our validation sample, Figure 2 presents the conditional item probabilities for each behavioral profile. These conditional item probabilities are provided in seven stacked bar graphs. Each bar graph presents the abbreviated names for each latent class indicator along the  $x$ -axis, while the probabilities of endorsing each item are evident along the  $y$ -axis. The first seven items in each plot are categorical items that measure student engagement in school-sponsored ECAs (i.e., sports, intramural, arts, service, voclub, saclub, and comserve). These variables have two response categories (0, 1). For these manifest variables, the gray bars indicate the probability of endorsing the second response category (1).

The rest of the manifest variables included in our analyses are ordinal items. Seven of these ordinal items have three response categories (0, 1, 2)—only the *read* variable is coded to include two response categories. For the three-response-category ordinal items (i.e., *ecin*, *ost\_in*, *tv\_vid*, *hw*, *cut*, *abs*, and *susp*), the dark regions of the bars depict the probability of endorsing the third response category (2), and the gray-shaded regions depict the probability of endorsing the second response category (1). As noted earlier, the items

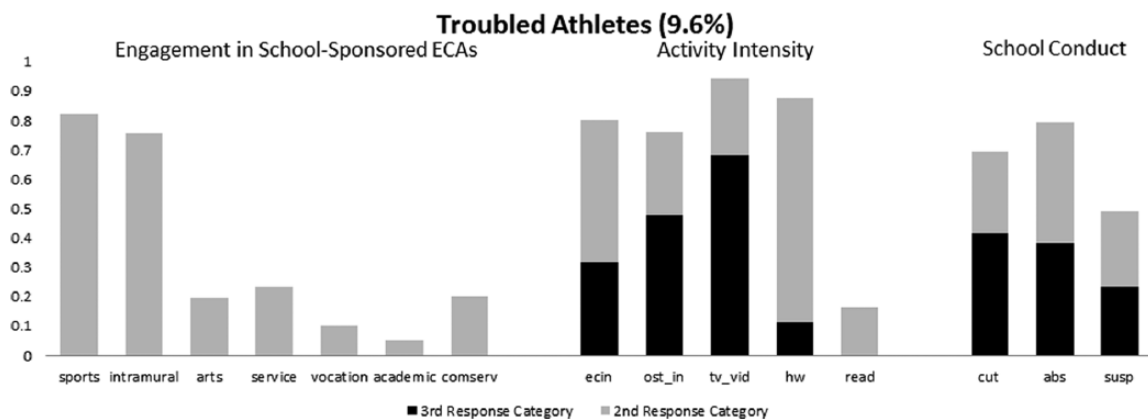
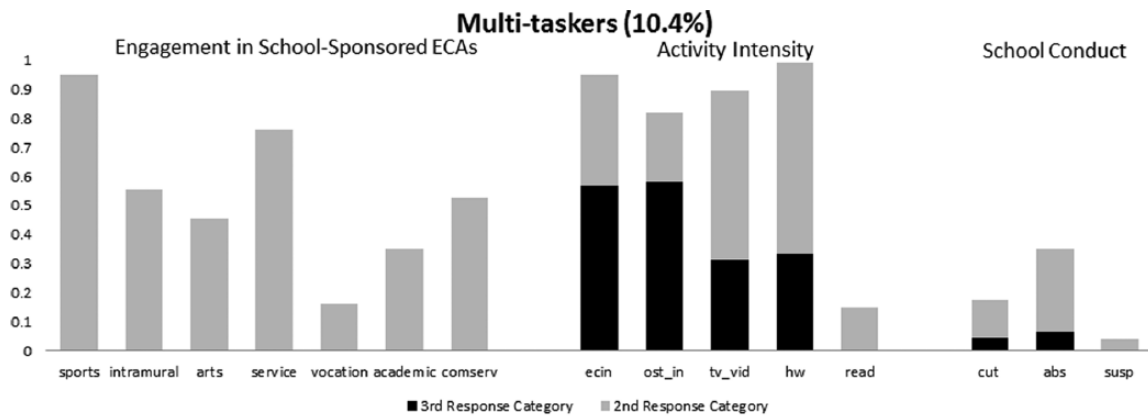
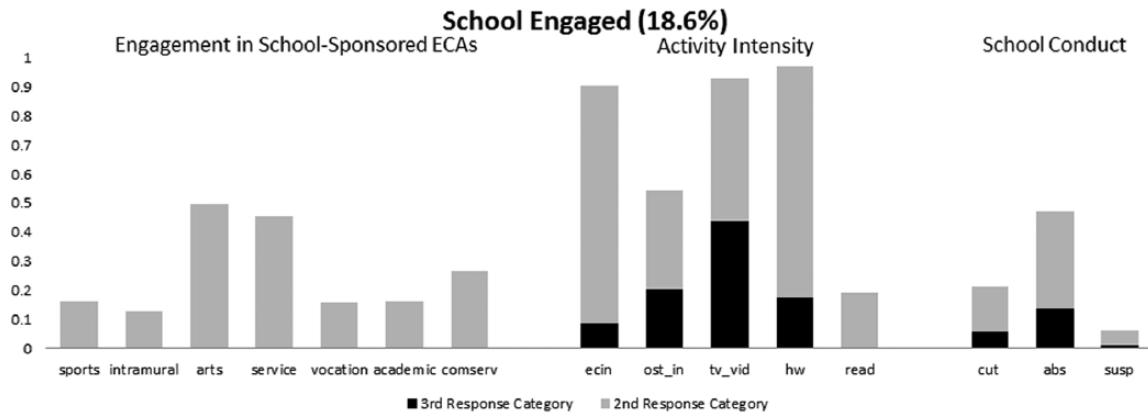
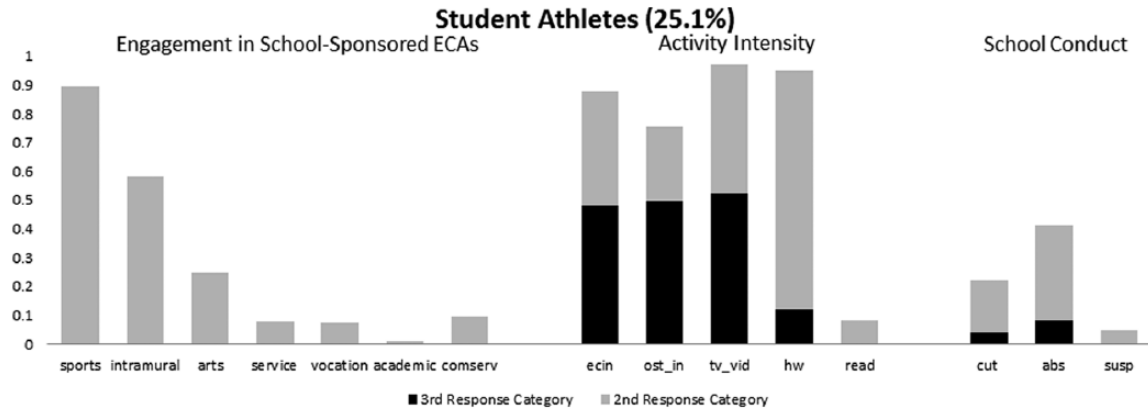
are grouped according to the subdomains of students' behavioral engagement identified in the Method section. The corresponding labels for each of these subdomains are noted across the top of the stacked bar groupings.

*The Student Athletes.* The first behavioral profile culled from our analysis was estimated to represent a quarter of our validation sample (25.1%). It consists of students who participated in both interscholastic and intramural sports at the school as well as structured ECAs in the community. We refer to this behavioral profile as the *Student Athletes*. This class closely mirrors Linver et al.'s (2009) "sports-only" cluster as well as the "jock" student identity identified in Eccles and Barber's (1999) Breakfast Club study.

As shown in Figure 2, Student Athletes tend to engage in school- and community-based activities with moderate to high intensity. Nearly 90% of Student Athletes participated in school-based (and mostly sports-oriented) ECAs at least 1 hour per day (*ecin*), with 50% engaged in school-based ECAs for more than 2 hours per day. In addition, an estimated quarter of Student Athletes engaged in community-based ECAs once a week, while about half of these students engaged in community-based activities at least twice a week (*ost\_in*).

Beyond participation in ECA's, most Student Athletes (83%) devoted 1 to 2 hours a day to their homework. About half watched television or played video games for 4 or more hours each day. Finally, as evident in Figure 2, students belonging to the Student Athletes profile were unlikely to experience behavioral challenges at school.

When examined holistically, the behavioral patterns of the Student Athletes class reflect a kind of behavioral engagement that can be characterized as concentrated school-community engagement. Here, *school-community*



(continued)

FIGURE 2. (continued)

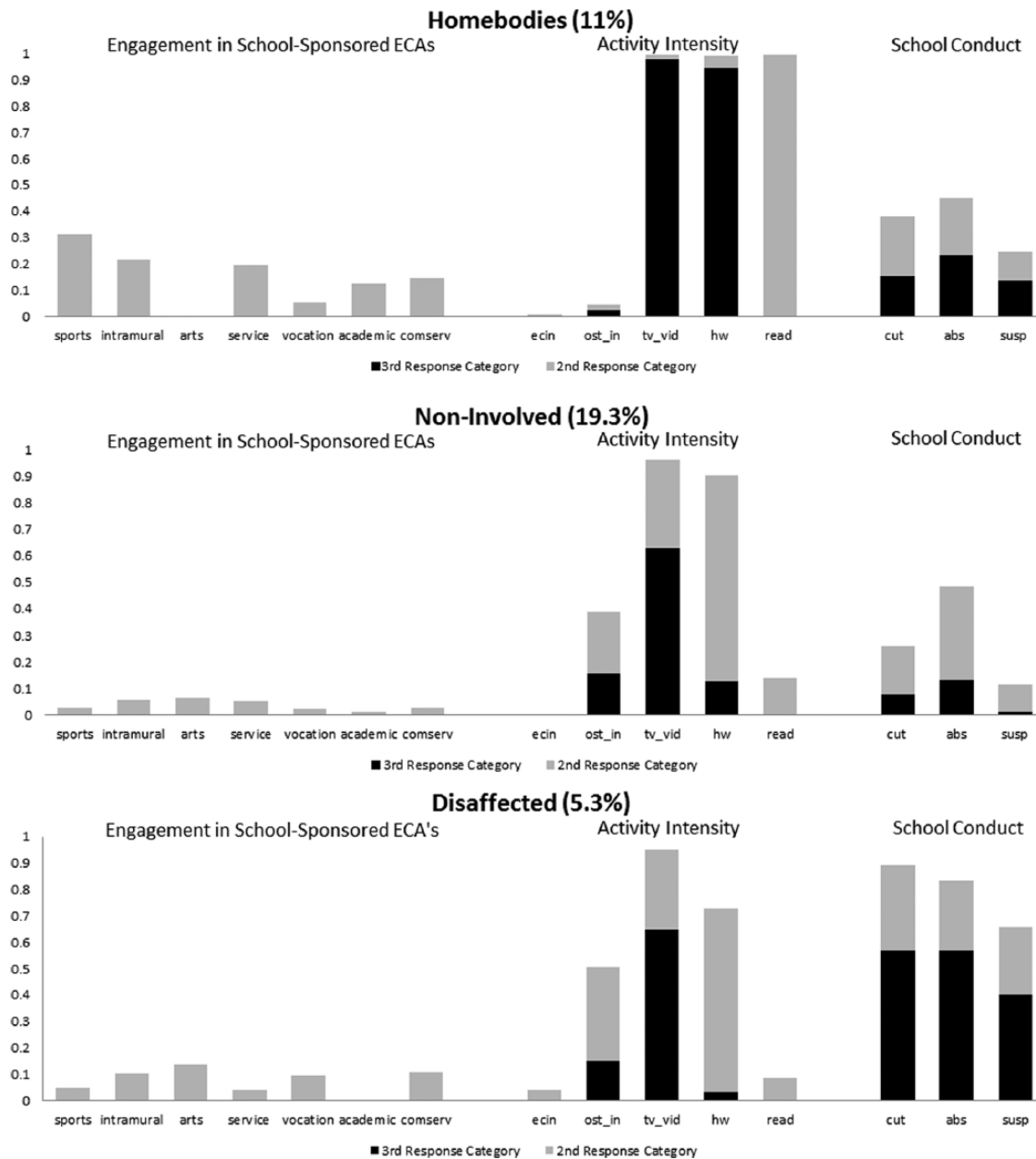


FIGURE 2. Profiles of students' behavioral engagement.

*engagement* refers to student tendencies to participate in organized activities at school and in the community. The adjective *concentrated* describes student tendencies to engage in activities that revolve almost exclusively around sports. By virtue of this kind of behavioral engagement, research suggests that students who belong to the Student Athletes class may gain access to important social resources, opportunities, and networks (peer groups, friends, adults)

that they can leverage to enhance their social-academic standing and overall school success (e.g., Fredricks & Eccles, 2006).

*The School Engaged Profile.* The second behavioral profile yielded from LCA was estimated to represent nearly 20% of our validation sample. We refer to this profile as the *School Engaged* class because it consists of students who

participated in school- and community-based ECAs that did not involve sports. Empirically, this profile appears very similar to the “school groups” cluster first identified by Linver et al. (2009).

As evident in Figure 2, students who belong to the School Engaged behavioral profile appear the most drawn to school-based arts and service activities. Nearly 90% of these students participated in these school-based activities for at least an hour a day. Significantly, about half of these students supplemented their engagement in school-based ECAs with participation in community-based ECAs. However, in contrast to the high-intensity engagement demonstrated by the Student Athletes, students in the School Engaged class generally engaged in these community-based activities less than twice a week.

Beyond their ECA engagement, students in the School Engaged class generally devoted 1 to 2 hours a day to their homework. About 45% of these students watched television or played video games for 4 or more hours a day. Last, as shown in Figure 2, these students were unlikely to experience behavioral difficulty at school.

When viewed in the round, the students’ behavioral patterns of the School Engaged class reflect a kind of behavioral engagement that might be called low-intensity school-community engagement. This kind of engagement reflects the tendency of these students to spend less time participating in ECAs than the other ECA-related behavioral profiles. Readers should remain mindful, however, that the “low-intensity” nature of this engagement may simply represent an artifact of the time requirements needed for school arts and service activities relative to sports and perhaps the logistical challenges of engaging in out-of-school community-based ECAs (Bohnert et al., 2010). The benefits and competencies yielded from these activities may be similar to that of higher-intensity ECAs.

*The Multitaskers.* The third behavioral profile culled from our analyses was estimated to represent about 10% of our validation sample. It consists of students engaged in a broad range of activities (both sports and nonsports related) at school and in the community. We refer to this group as the *Multitaskers*. This behavioral profile closely resembles the “sports-plus” cluster yielded by Linver et al.’s (2009) study.

The Multitaskers can be readily identified by the breadth of their behavioral engagement across settings. For instance, about 90% of the Multitaskers engaged in school sports, while 75% engaged in school service clubs. In addition, 45% of the Multitaskers participated in school-sponsored arts activities, and over 50% were engaged in community service. Significantly, the multitaskers generally engaged in these activities with high levels of intensity: Nearly 60% of these students engaged in school-based ECAs for more than 2 hours a day.

In addition to their school engagement, nearly 90% of the Multitaskers reported engagement in community-based ECAs. In fact, 60% of these students participated in community-based ECAs at least twice a week. This finding indicates that the majority of Multitaskers engaged in both school and community-based ECAs with levels of high intensity.

Beyond their engagement in constructive leisure activities at school and in the community, the multitaskers generally devoted 1 to 2 hours each day to homework. Although they were unlikely to read outside of school, they often engaged in fewer hours of relaxed leisure activities than the other behavioral profiles. They were also unlikely to experience behavioral problems at school.

When examined holistically, the behavioral patterns of the Multitaskers reflect a kind of behavioral engagement that might be characterized as high-intensity/high-breadth school-community engagement. Research indicates that the high-intensity/high-breadth nature of this engagement may provide the Multitaskers with a broad range of skills, competencies, and social contacts that can be leveraged for school success (Bohnert et al., 2010; Gardner et al., 2008).

*The Troubled Athletes.* The fourth behavioral profile was estimated to represent nearly 10% of our validation sample. We refer to this profile as the *Troubled Athletes*. Students who belong to the Troubled Athletes class had about a 70% chance of cutting class at least once during the first semester of 10th grade, while about 80% of this profile was absent three or more times during the same time period. In addition, nearly a quarter of the Troubled Athletes were suspended three or more times during the first semester of their sophomore year in high school.

Beyond their vulnerability for school difficulty, the Troubled Athletes generally engaged in sports-oriented school- and community-based ECAs. For instance, the vast majority of the Troubled Athletes engaged in interscholastic (84%) and intramural sports (75%) activities at the school. In addition, the Troubled Athletes generally engaged in community-based ECAs with the same estimated intensity as the Student Athletes behavioral profile.

In home settings, nearly 70% of the Troubled Athletes class watched television or play video games for more than 4 hours a day. In addition, while the Troubled Athletes were unlikely to report reading outside of school, they generally devoted 1 to 2 hours a day to their homework.

When viewed together, the behavioral patterns of the Troubled Athletes reflect a kind of engagement that might be categorized as selective school-community engagement with the risk of academic disaffection. The engagement of the Troubled Athletes was “selective” because their overall conduct patterns did not appear to fit very well with the norms, habits, and routines prioritized by their high schools. However, this tendency for behavioral difficulty did

not preclude these students from engaging in other formal activities in the school and/or community. For this reason, the social and educational outcome trajectories of the Troubled Athletes may be particularly especially fluid when compared to other behavioral profiles. Some of these students may present ongoing risks for school difficulty, while others may leverage their ECA engagement to help them stay in school, graduate, and pursue postsecondary careers (e.g., Mahoney, 2000).

*The Homebodies.* The fifth behavioral profile culled from our analysis was estimated to represent 11% of our validation sample. This behavioral profile consists of students with unusually high chances of engaging in academically and educationally relevant activities in home settings. In light of this key engagement-related feature, we refer to this profile as the *Homebodies*.

As shown in Figure 2, nearly 95% of the Homebodies engaged in homework activity for 2 or more hours a day—which was the highest among all seven behavioral profile groups. In addition, while the Homebodies had exceptionally high chances (98%) of watching television or playing video games for 4 or more hours each day, nearly all of these students read material that was not assigned by the school. This characteristic was significant because the Homebodies were the only student subpopulation that reported consistent engagement in reading as a (constructive) leisure activity.

When viewed together, the academically oriented behaviors of the Homebodies behavioral profile reflect a kind of behavioral engagement that might be characterized as high-intensity academic engagement. At first glance, these students appear to represent the most likely candidates to have engagement dispositions characterized by academic enjoyment, interest, and efficacy. They also appear the best positioned to experience academic success.

*The Non-Involved.* The sixth behavioral profile was estimated to represent nearly 20% of our validation sample. It consists of students who generally did not report engagement in school- or community-based ECAs. We refer to this behavioral profile as the *Non-Involved*. Empirically, this group closely mirrors the “low-involved” cluster identified in the Linver et al. (2009) study.

As shown in Figure 2, Non-Involved students generally engaged in the same breadth activities as the homebodies (watching TV, playing video games, and doing their homework), although they generally did so with less intensity. Non-Involved students were also similar to the homebodies in that they presented low risk for conduct problems at the school.

In light of these engagement-related characteristics, the behavioral patterns exhibited by Non-Involved students appear to reflect a kind of behavioral engagement that might be characterized as low-intensity academic engagement.

This low-intensity academic engagement was characterized by these students’ tendencies to devote at least an hour each day to academic work as well as their overall lack of conduct problems at the school. At the same time, the more limited breadth and intensity of their school engagement were noteworthy, especially since these students represent a considerable portion of the American (public) high school population.

*The Disaffected.* The seventh behavioral profile was estimated to represent 5.3% of our validation sample. We refer to this class as the *Disaffected* because it included students with significant histories of behavioral challenges at school. Conceptually, this profile closely resembles Eccles and Barber’s (1999) “criminals” identity.

As shown in Figure 2, students who belong to the Disaffected profile generally did not engage in school-based ECAs. However, nearly half of these students reported engagement in community-based ECAs. Beyond ECA engagement, nearly two thirds of students in the Disaffected profile watched television or play video games for 4 or more hours a day. About 30% of these students did not engage in homework activity.

Last and most significantly, these students were especially vulnerable to experiencing behavioral problems at school. For instance, students in the Disaffected profile had nearly a 90% chance of cutting class at least once, while an estimated 56% of this class reported skipping class three or more times in the first quarter/semester of their sophomore year in high school. In addition, 56% of Disaffected students reported that they missed school seven or more times during the first quarter/semester of their 10th-grade year, while nearly 40% were suspended three or more times during the same time period.

When viewed in the round, the behavioral difficulties experienced by the Disaffected appear to reflect a kind of behavioral engagement that can be characterized as high-intensity behavioral disengagement from school. This behavioral disengagement is notable because of its known relationship to early school leaving and overall school failure (e.g., Henry, Knight, & Thornberry, 2012; Rumberger & Rotermund, 2012). At the same time, the community-based activities reported by these students should not be ignored. Because more than 50% of these students play nonschool sports, take sports lessons, and/or take music, arts, or language lessons in the community, they should be viewed as possessing competencies that can be leveraged to promote their school engagement and academic success.

#### *Student Background Factors and Behavioral Profile Membership*

In this section, we present the results of a multinomial logistic regression of students’ behavioral engagement on

TABLE 3

*Estimated Probability of Behavioral Profile Membership by Student Background Characteristics (N = 12,760)*

Variable	Student Athletes (25%)	School Engaged (18%)	Multitaskers (12%)	Troubled Athletes (8%)	Homebodies (11%)	Non- Involved (17%)	Disaffected (9%)
Student ethnicity							
African American	0.363	0.190	0.058	0.021	0.058	0.176	0.134
Hispanic	0.284	0.180	0.052	0.020	0.054	0.253	0.156
Asian	0.228	0.369	0.033	0.013	0.034	0.221	0.102
Other	0.339	0.229	0.044	0.017	0.046	0.181	0.143
White	0.267	0.177	0.142	0.055	0.148	0.138	0.073
Student gender							
Male	0.316	0.142	0.093	0.080	0.106	0.166	0.098
Female	0.236	0.220	0.164	0.058	0.093	0.146	0.083
Student SES							
5th percentile	0.091	0.070	0.012	0.047	0.513	0.161	0.106
10th percentile	0.231	0.164	0.058	0.082	0.109	0.221	0.135
25th percentile	0.271	0.186	0.086	0.082	0.049	0.204	0.121
50th percentile	0.299	0.200	0.119	0.079	0.021	0.179	0.103
75th percentile	0.320	0.206	0.166	0.071	0.008	0.147	0.082
Prior academic history: Ninth-grade GPA							
1.0	0.169	0.180	0.023	0.115	0.178	0.159	0.175
2.0	0.225	0.267	0.059	0.072	0.133	0.151	0.093
3.0	0.253	0.334	0.127	0.038	0.084	0.122	0.042
4.0	0.244	0.360	0.234	0.017	0.045	0.084	0.016

Note. SES = socioeconomic status; GPA = grade point average.

TABLE 4

*Wald Test of Parameter Constraints*

Variable	Wald Chi-Square	p Value
Student ethnicity	91.215	<.001
Student gender	70.191	<.001
Student SES	632.229	<.001
Ninth-grade GPA	515.689	<.001

Note. SES = socioeconomic status; GPA = grade point average.

their ninth-grade GPA, SES, race/ethnicity, and gender. These results are provided in Table 3. As noted earlier, these results are provided using the model-estimated class proportions for each predictor's critical values (adjusted for the other predictors) rather than individual regression coefficients (i.e., conditional log odds ratios). Readers should be mindful that because these analyses were conducted using imputed data sets involving the full ELS sample of public high school students ( $N = 12,760$ ), the estimated proportion of students belonging to each behavioral profile differs slightly from the results reported above. These "revised" estimates can be found at the top of each column in the table. Results from our Wald tests of parameter constraints can be located in Table 4.

*Ethnicity and Behavioral Profile Membership.* The top set of results in Table 3 present the model-estimated probability for behavior class membership by student ethnicity, controlling for gender, SES, and students' ninth-grade GPA. These analyses show that African American and Hispanic students were unlikely to experience behavioral difficulty when they were engaged in school- and community-based ECAs, all else equal (e.g., Feldman & Matjasko, 2005). They also show that African American and Hispanic students were among the most likely candidates to experience behavioral difficulty when they were not engaged in formal ECAs at school.

Meanwhile, White students had the highest relative chances of belonging to the Multitaskers behavioral profile. This finding indicates that White students may not only be especially well positioned (and coached) to take advantage of those opportunities; they may also live in school communities where those opportunities are the most present (Sharkey, 2009).

Finally, our findings painted an alternative portrait of the behavioral engagement patterns of Asian students, a portrait that runs counter to a conventional stereotype. Although this stereotype might prompt the assumption that Asian students would be highly represented in a behavioral profile characterized by high-intensity academic engagement, our models

provide a different picture. In fact, Asian students had the lowest chances of belonging to the behavioral profile that best fit those behavioral patterns (i.e., the Homebodies). Moreover, these same Asian students had the highest combined chances of belonging to a behavioral profile characterized by ECA-oriented school engagement.

*Gender and Behavioral Profile Membership.* The second set of results provided in Table 3 present the model-estimated probabilities of behavioral profile membership by student gender, controlling different students' ethnicities, SES, and students' ninth-grade GPA. As evident in Table 3, these models revealed important gender differences in the Student Athletes, School Engaged, and Multitaskers profiles. For instance, males had higher chances than females of belonging to the Student Athletes profile (31.5% to 23.6%). In contrast, females had higher chances of belonging to the School Engaged (21.9% to 14.2%) and Multitaskers (16.4% to 9.2%) profile groups. More broadly, males were only slightly more likely than females (18% vs. 14%) to belong to a behavioral profile group characterized by school conduct problems (i.e., the Troubled Athletes and Disaffected profiles).

*Student SES and Behavioral Profile Membership.* The third set of results in Table 3 present the model-estimated probabilities of membership in behavioral engagement profiles by discrete levels of students' socioeconomic standing, adjusting for student ethnicity, gender, and students' ninth-grade GPA. As evident in Table 3, the influence of SES varied among the different behavioral profiles culled from our analyses. Although student SES was used as a continuous predictor of behavioral engagement class membership in the model, the practical importance of this association is most evident when the class distribution is viewed at these discrete SES levels.

For instance, students who were in the 5th percentile of SES had more than a 50% chance of belonging to the Homebodies profile group, all else equal. However, once students' SES standing increased beyond the 5th percentile, the model estimated chance of belonging to the Homebodies profile decreased precipitously, such that students in the 50th SES percentile were estimated to have only a 2% chance of belonging to that activity group, all else equal. At first glance, this finding was both striking and unexpected; we did not anticipate that the behavioral profile characterized by the most robust academic engagement (i.e., the Homebodies) would be disproportionately represented by the most economically poor students attending public high schools in the United States.

In addition to the Homebodies, there was other evidence that suggests that students' behavioral engagement patterns may be stratified by SES. Specifically, as shown in Table 3, our model indicated that students in the 5th percentile of the

SES distribution enjoyed only a 22% chance of belonging to the Student Athletes, School Engaged, or Multitaskers profile groups, *ceteris paribus*. However, when students reached the 25th percentile of the SES distribution, they had nearly a 62.5% chance of belonging to one of these groups. Significantly, this chance increased to 75% for students in the top quartile of SES.

Finally, while student SES represented an important predictor for membership in the Student Athletes, School Engaged, and Multitaskers profiles, it was notable that it was not a strong predictor for behavioral difficulty at school, all else equal. Specifically, although the chance of belonging to the Disaffected behavioral profile was the smallest for students from the wealthiest families, the probability of belonging to the Troubled Athletes class was relatively constant for students with SES values that fell between the 10th and 75th percentiles of the SES distribution. These findings indicate that SES is associated with enhanced opportunities for ECA engagement. It does not appear strongly associated with behavioral disaffection when student gender, ethnicity, and prior academic performance are controlled in the statistical model.

*Prior Academic History and Behavioral Profile Membership.* The final set of results in Table 3 present the model-estimated probabilities of behavioral profile membership by discrete levels of student ninth-grade GPA in core academic subjects, adjusting for student ethnicity, gender, and SES. Similar to SES, GPA was used as a continuous predictor of behavioral engagement class membership in the model, but we present the class distribution at meaningful points on the GPA scale. As shown in Table 3, our models supported a generally positive relationship between ninth-grade GPA and membership in the Student Athletes, Multitaskers, and School Engaged behavioral profiles. In contrast, our models yielded an inverse relationship between ninth-grade GPA and belonging to the Troubled Athletes, Homebodies, Non-Involved, and Disaffected behavioral profiles, all else equal. Specifically, students who received a 1.0 GPA in ninth grade were estimated to have nearly a 30% chance of belonging to the Troubled Athletes or Disaffected profile groups, all else equal. Meanwhile, students who earned a 4.0 GPA in ninth grade were estimated to have only a 3% chance of belonging to these behavioral profiles. Thus, students who perform well academically had virtually no chance of belonging to those behavioral profile groups characterized by moderate-to-severe behavioral challenges at school, all else equal.

While low prior academic performance was associated with elevated risk of membership in profiles characterized by later conduct challenges, low prior academic performance was also associated with membership in profiles that did not include engagement in school-based ECAs. Specifically, students with a 1.0 GPA in ninth grade were

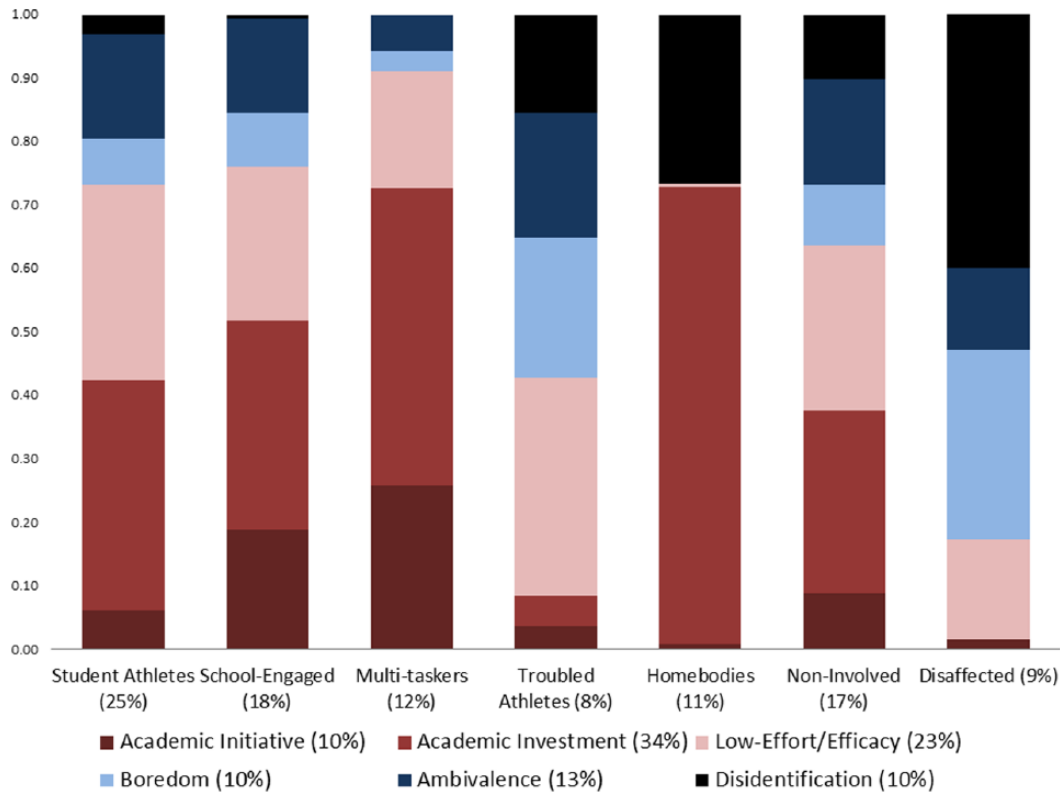


FIGURE 3. *Relational profiles of students' social-ecological engagement.*

estimated to have a nearly 34% chance of belonging to the Homebodies or Non-Involved profiles compared to the 13% chance of their 4.0-GPA peers.

#### *Profiles of Students' Social-Ecological Engagement*

The next statistical model analyzed intersections (i.e., the joint distribution) of students' dispositional and behavioral engagement profiles. The results of this analysis are presented graphically in Figure 3 as a stacked bar graph. In this figure, student membership in each of the seven behavioral profile groups is represented along the *x*-axis. The *y*-axis then depicts the conditional probability of belonging to student engagement disposition class *k* given membership in behavioral profile *j*. The results are further summarized in Table 5, showing the model-estimated joint and conditional probabilities of dispositional and behavioral profiles.

Overall, this "relational" profile model yielded two significant research findings. The first such finding pertained to the sheer diversity of students' engagement experiences. Specifically, out of the 42 possible behavior-by-disposition profile intersections that were analyzed in this model, 31 had model-estimated joint probabilities greater than 0.5% (see Table 5, "Cell %"). This finding was noteworthy because it provides an important empirical reminder that students' behaviors represent only one component of their

engagement; their thoughts, feelings, and identity beliefs also stand as important, characteristic features of their engagement and overall school experiences.

The second finding that can be derived from this relational model pertains to the dispositional patterns that were evident within each behavioral profile (see Table 5, "Column %"). Here, our results indicated that students who were engaged in ECAs and did not get in trouble at school (i.e., Student Athletes, School Engaged, and Multitaskers) often had the most optimal dispositions toward school and schooling (i.e., they often belonged to the academic initiative or investment classes). Moreover, as shown at the top of Figure 3, these students were also the least likely candidates to have engagement dispositions characterized by ambivalence and dis-identification. In fact, in these models, students who belonged to the School Engaged and Multitaskers profiles had virtually no chance of dis-identifying with school.

In contrast, as indicated by the blue and black shaded bars in Figure 3, students in the Troubled Athletes, Homebodies, Non-Involved, and Disaffected profiles had the highest combined chances of belonging to those disposition groups characterized by ambivalence, boredom, or academic dis-identification (Finn, 1989; Skinner & Pitzer, 2012). Moreover, with the notable exception of the Homebodies, students in these behavioral groups had relatively low chances of belonging to either the academic initiative or academic

TABLE 5

*Model-Estimated Intersection of Disposition Profile Membership (CED) and Behavioral Profile Membership (CEB): Joint Distribution (Cell %), CED Conditional on CEB (Column %), and CEB Conditional on CED (Row %), in Percentages (N = 12,760)*

Engagement Disposition Profile (CED)	Engagement Behavioral Profiles (CEB)							Overall
	Student Athletes	School Engaged	Multitaskers	Troubled Athletes	Home-bodies	Non-Involved	Disaffected	
Pr(CED ∩ CEB): Cell %								
Academic investment	9	6	6		8	5		34
Academic initiative	2	3	3			2		10
Low-effort/efficacy	8	4	2	3		4	1	23
Boredom	2	2		2		2	3	10
Ambivalence	4	3	1	2		3	1	13
Disidentification	1			1	3	2	3	10
Overall	25	18	12	8	11	17	9	100
Pr(CED   CEB): Column %								
Academic investment	26	16	24	34	1	19	31	34
Academic initiative	17	13	15	20		6	16	10
Low-effort/efficacy	9	2	19	4	1	26	6	23
Boredom	10	40	1	16	26		3	10
Ambivalence	29		33	5	72	47	36	13
Disidentification	10	30	9	22		3	7	10
Overall	100	100	100	100	100	100	100	100
Pr(CEB   CED): Row %								
Academic initiative	26	17	17	1	24	14		100
Low-effort/efficacy	15	33	32	3	1	15	1	100
Boredom	33	19	10	13		19	6	100
Ambivalence	18	16	4	19		17	26	100
Disidentification	31	20	5	13		22	9	100
Overall	7	1		13	29	17	34	100
Academic initiative	25	18	12	8	11	17	9	100

*Note.* Percentages less than 0.5 are not printed.

investment disposition profile groups. This finding was important because it indicated that an overall lack of engagement in constructive leisure activities can limit students' academic engagement and overall school identification.

*Examining Students' Social-Ecological Engagement as a Higher-Order Construct.* Although the joint distribution of dispositional and behavioral profiles provided in Table 5 and Figure 3 provide an important, fine-grained view of students' overall engagement experiences, their endemic complexity makes them less than useful for intervention planning and policy development. Therefore, in order to provide a more parsimonious view of students' social-ecological engagement, we explored an alternative measurement specification. In this approach, we fit an LCA model that specified our behavioral and disposition profiles as indicators of a higher-order latent construct that we labeled *students' social-ecological engagement*.

As detailed in Appendix E, five characteristically distinct profiles of students' social-ecological engagement were

yielded from this higher-order LCA approach. A graphic depiction of these profiles is provided along a panel of bar graphs in Figure 4. A brief summary follows.

The first higher-order social-ecological profile was estimated to represent 8% of the ELS sample. It consists of students who belong mostly to the academic initiative disposition profile (75%) as well as the School Engaged and Multitaskers behavioral groups (70%). We refer to this social-ecological profile as the "school initiative" class because of these students' apparent intrinsic enjoyment of, and identification with, both ECAs and academics (see also Larson, 2000).

The second social-ecological profile was estimated to represent 28% of the ELS student sample. This group consists almost entirely of Student Athletes, School Engaged, and Multitaskers who have engagement dispositions characterized by a strong belief in the overall importance of school and schooling. We refer to this group as the "school investment" class because of these students' apparent commitments to both

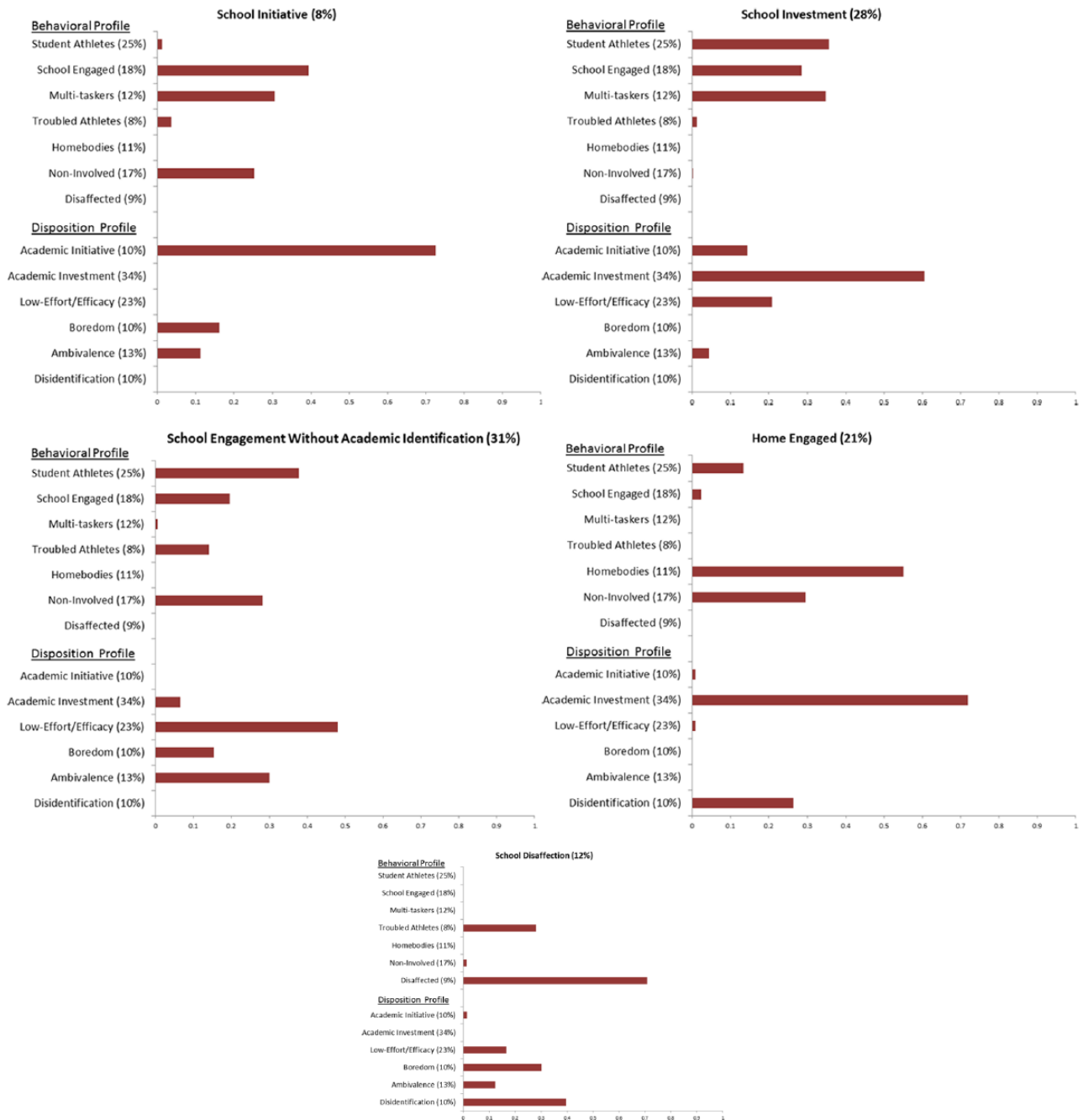


FIGURE 4. Higher-order profiles of students' social ecological engagement.

academics and constructive leisure activities at school. Readers should be mindful, however, that by virtue of having an 80% chance of belonging to either the academic investment (60%) or low-effort/efficacy disposition (20%) groups, most of these students do not, on the whole, enjoy academic work. For this reason, this profile should be considered characteristically distinct from the school initiative class, which tends to exhibit the most authentic form of academic identification.

The third social-ecological profile was estimated to represent 31% of the ELS student sample. This group

consists mostly of students in the Student Athletes, School Engaged, Troubled Athletes, and Non-Involved behavioral groups who belong to either the low-effort/efficacy (48%) or ambivalence (30%) disposition profiles. Because most of these students approach academic work without much enjoyment or efficacy, we labeled this social-ecological profile the "school engagement without academic identification" class, with the reminder that this *lack of identification* is not synonymous with academic *dis-identification*.

The fourth social-ecological profile included 21% of the ELS student sample. This profile consists mostly of students who belong to either the Homebodies or Non-Involved behavioral profile groups. Because these students' behavioral engagement preferences were rooted in the home, we characterized this profile as the "home engaged."

Although these students shared similar home-based behavioral engagement patterns, an analysis of these students' engagement dispositions suggests that this profile includes, at minimum, two primary engagement subtypes. The first subtype includes the 70% of home-engaged students who have engagement dispositions characterized by academic investment toward school. The second subtype includes the 30% of Homebodies and Non-Involved students who dis-identify with academics and school overall. Presumably, these sharp differences in engagement dispositions stand as important predictors for these students' long-term educational outcome trajectories (e.g., Eccles et al., 2003; M. Lawson & Masyn, 2015).

The fifth and final social-ecological profile was estimated to represent 12% of the ELS student sample. This profile consists almost entirely of Disaffected (70%) students and Troubled Athletes (28%) who also belong to the dis-identification (39%), boredom (30%), or ambivalence (12%) disposition profile groups. Because these students seem behaviorally, cognitively, and emotionally dissatisfied with school and academic work, we labeled this profile the "school disaffected."

Although research and theory indicate that students in the school-disaffected profile are the most likely candidates for school failure and other social problems (Eccles et al., 2003; Henry et al., 2012), the range of dispositions included in this group indicate that this profile is not a monolith. In fact, some of these students (i.e., Troubled Athletes and Disaffected) possess engagement-related strengths and competencies that might be used to foster their academic engagement, reengagement, and overall school success.

### Contributions and Conclusions

This study was designed to explore a novel conceptual-analytic model for student engagement research. Drawing on the work of M. Lawson and Lawson (2013), this model depicted student engagement as the intersection between students' behavioral engagement in school, home, and community settings and their thoughts, feelings, attitudes, and identity beliefs about school—that is, their engagement dispositions. LCA was used to analyze these constructs and their relations using data drawn from a nationally representative sample of students attending public high schools in the United States.

We began this study with a core assumption—namely, that we would find a strong link between student behavioral

profiles characterized by engagement in constructive leisure activities at school, at home, and in the community and engagement dispositions characterized by academic engagement in schools and classrooms. This assumption was founded primarily on Jeremy Finn's (1989) participation-identification model of engagement. This model predicts a recurrent pattern: Behaviorally engaged students will identify with school, while behaviorally disengaged students will not.

Results from this study indicate that the participation-identification relationship modeled by Finn (1989) is not simple or automatic. To the contrary, it appears significantly more nuanced than originally proposed. This study serves to affirm, amend, and extend Finn's model while also highlighting the complexity of the participation-identification relationship as nonlinear and nonhomogeneous.

Four primary conclusions help to categorize this relationship and its endemic complexity. First, for many students, participation does not uniformly or equivocally lead to academic engagement or identification. This conclusion was grounded in a finding presented earlier, that is, 31% of students belonged to the "school engagement without academic identification" social-ecological profile. It was also evident in the approximately 30% of Homebodies who dis-identified with academics and school overall. Together, these two profiles suggest that educational interventions that proceed with a strict behavioral focus may be destined to fall short of their desired outcomes.

The second conclusion is that, in the main, student participation in ECAs all but eliminates the probability of school dis-identification. This conclusion follows models that indicated that students in the School Engaged, Multitasker, and Student Athletes profiles had virtually no chance of belonging to the disposition profile characterized as dis-identification. Together, these profile findings indicate that although student participation in ECAs may not be by itself sufficient for academic identification, it may act as critical safeguard against the problems associated with disengagement, starting with dropout and encompassing other forms of social withdrawal (e.g., Henry et al., 2012).

The third conclusion is that while behavioral difficulty all but eliminates the prospect of academic engagement and identification, it seldom leads to school dis-identification. Here, our relational models indicated that a large majority of Disaffected students and Troubled Athletes belong to a disposition group other than the dis-identification class. This finding is important because it signals considerable interstudent variability among students with persistent conduct problems. The ready implication is that one-size-fits-all behavioral interventions for so-called troubled students are unwarranted. Indeed, formulaic interventions universally applied to all manner of students have the potential to cause harm (Ferguson, 2001).

The fourth conclusion is consistent with Finn's (1989) prediction. That is, with only a few exceptions, academic

identification operates in synergy with participation. This important relationship was especially evident in our analysis of the behavioral patterns of students in the academic initiative class—that is, the student subgroup that intrinsically identified with academics and school overall. Here, the data indicated that 83% of those in the academic initiative class belonged to a behavioral class characterized by participation in school-based ECAs.

In summary, our findings indicate that while participation does not ensure identification (e.g., only 29% to 43% of Student Athletes, School Engaged, and Multitaskers were in the academic initiative or academic investment disposition classes), academic identification nearly always includes some sort of school-community engagement and participation. Thus, in its most optimal form, student engagement might be best characterized as identification-participation. One implication is that in order to facilitate more optimal forms of academic engagement and identification in schools and classrooms, educational policy and practice may need to prioritize the development of students' identity-related drivers (i.e., their engagement dispositions), with particular attention toward how these drivers might be fortified by students' behavioral engagement in constructive leisure activities at school, at home, and in the community (M. Lawson & Lawson, 2013).

#### *The Importance of Identity Transfer and Stage-Environment Fit*

The preceding discussion implicates a promising engagement strategy, one that helps students transfer their engagement and identification from one activity setting to others. To realize this promise, educational leaders and policymakers will need to invest in three related educational practice and policy priorities. The first is to create opportunities for every student to engage in a structured leisure activity of their interest either at school or in the community (Oyersman et al., 2011). This priority follows findings that indicated that participation and engagement in school-based or community-based ECAs provides a safeguard against school disengagement, dis-identification, and social withdrawal. For this reason, ECA engagement appears to represent a promising strategy for enhancing high school completion outcomes (Skinner & Pitzer, 2012), especially for the 1,500 American public high schools dubbed as “dropout factories” (Balfantz & Byrnes, 2012).

The second educational policy and practice priority is to create more robust opportunities for “skill, competency, and identity transfer” (e.g., Larson, 2000). This need is evident because of the uneven synergy that appears to exist between students' ECA/school engagement and their academic engagement in schools and classrooms. Although our findings indicate that ECAs can help to ignite this synergy, they also indicate that more explicit transfer strategies are needed, especially ones that connect students' students' extraschool

interests and identities to academics and formal classroom settings (e.g., Nasir & Hand, 2008).

The third policy priority is for educational leaders and policymakers to help synchronize opportunities for engagement across school, home, and community settings. To realize this objective, schools, families, and community agencies will need to work together to create social environments that “fit” the developmental needs and priorities of today's diverse high school student populations (Eccles & Roeser, 2011). As stage-environment fit theorists suggest (e.g., Eccles, 2014), this fit can best be facilitated by enhancing student access to five related kinds of engagement opportunities: (a) opportunities for social interactions with adults and a positive peer group; (b) opportunities to exercise autonomy; (3) opportunities to develop educationally relevant skills, competencies, and interests; (d) opportunities for participation and contribution; and (e) opportunities for mattering.

What is striking about these opportunities is how at odds they may be with conventional “walled-in” school improvement models, especially those that emphasize standardized curricula and one-size-fits-all teaching and learning strategies. For this reason, improvement models characterized as partnership models (e.g., H. Lawson, 2014), community collaboration models (e.g., Anderson-Butcher et al., 2010), multiservice and extended-service schools (Dyson & Todd, 2010), and community schools (Blank, Berg, & Melaville, 2006) provide an attractive place-based alternative to more standardized models of schooling.

However, for these models to realize their promise, engagement will need to become an explicit improvement priority. Presently it is not, in part, because their improvement discourses tend to focus on health and social services or perhaps sharing decision-making power and authority with parents, young people, and other local residents (e.g., Ishimaru, 2014). In our view, these current models might be expanded from the current focus on removing barriers to engagement and learning (e.g., Adelman & Taylor, 2005), or more narrowly, preventing disengagement (Rumberger & Rotermund, 2012), to developing those setting-level characteristics and opportunities that are known to foster engagement by way of stage-environment fit (Eccles, 2014).

Finally, in order to help facilitate the synchronization and/or transfer of student engagement across home, school, and community settings, educational leaders, community, and youth development leaders will need to have access to expanded data sets. Here, local educational and social-health leaders, policymakers, and university faculty can take stock of the work undertaken by the Youth Data Archive (e.g., Nelson, London, & Stroebel, 2015) and develop data systems that track student engagement across schools, health and social service agencies, and local not-for-profit organizations. From there, researchers can use LCA to generate engagement profile models that can facilitate more comprehensive improvement planning and more nuanced policy development. Such is

the potential of person-centered research models that are guided by social-ecological frameworks.

### *Limitations and Future Directions*

We acknowledge several limitations. First, although the engagement profiles examined in this study appear well aligned with extant engagement research and theory, they are nonetheless dependent on the observed latent class indicators that were analyzed in this research. Thus, each of this study's engagement profiles might have significantly altered (or enhanced) if we had included other indicators in our latent class models. For this reason, future research can help test the stability and replicability of our profiles by analyzing other "manifest variables" of engagement, including measures of paid and unpaid work, household chores, and engagement in faith-based activities (e.g., Peck et al., 2008).

A second and related limitation concerns the quality of the observed latent class indicators that were used to estimate our behavioral engagement and engagement disposition profile models. For instance, although the ELS data set provides researchers with access to a diverse array of ECA engagement indicators, the ELS survey items used to capture these experiences were not written with time stems (e.g., "In the past 6 months, have you . . ."). Because of this omission, we were unable to discern whether our behavioral profile models reflected what students have done in school, what they are doing, what they plan to do, or some combination thereof.

Another potential limitation of this study relates to the analytic specification of our disposition profile models. This limitation was suggested by an *AERA Open* reviewer who questioned whether some of our engagement disposition variables were better classified as indicators of students' behavioral engagement. As others have noted (e.g., Fredricks et al., 2004), disentangling students' cognitions from their behaviors is especially challenging in survey research, where items like student "effort" and "persistence" can readily be interpreted as either an action (i.e., a behavior) or an orientation to action (i.e., a thought or an identity belief). We chose

to position these variables as indicators of students' engagement dispositions because we believe that students' attributions about their academic competence is best characterized as an identity belief rather than a specific, identifiable and/or verifiable behavior (see M. Lawson & Masyn, 2015, for a greater discussion of this issue). However, we recognize that others may disagree with this view. For this reason, future work should continue to test the construct validity of this study's engagement profile models using alternative measurement strategies and analytic specifications.

A third limitation of this study involves needs to better understand those social-ecological influences that contribute to the development of students' engagement behaviors and dispositions. Students' peer groups and peer group identities represent two such constructs (e.g., Busch et al., 2014). These variables were not included in this study because of constraints in the ELS data set. However, future research will benefit by examining their potential mediating role in shaping students' long-term engagement trajectories and educational outcomes.

Finally, future research should better attend to the localized conditions that facilitate (or constrain) engagement across students and schools. As a part of this effort, researchers can and should use local data to further test the content validity of the profiles advanced in this study. Such district- and countywide studies carry the potential to capture local patterns of engagement that may be silenced by this study's aggregated model. In this sense, it is helpful to think about this study's social-ecological profiles as a set of "ideal types" (Hearn, 1975). Viewed as ideal types, our profiles may not identify or capture the unique engagement-related characteristics of any particular student or case.

Notwithstanding these important design limitations, this study offered important insights into the heterogeneous nature of high school students' engagement experiences. And, as part of mapping these complex contingencies, this study helped frame a robust pathway for future engagement research and practice, one that privileges inquiry into the mechanisms that facilitate student engagement in school-community life.

## **Appendix A**

### *Variable Names and Codes for Indicators of Disposition Profile Membership*

Variable	Scale	ELS:2002 Variable and Description	ELS Coding
Students' future beliefs			
Postsecondary initiative (psin)	0 = Use informal resources only 1 = Used one or more formal resource 2 = Used formal and informal resources (student self-report)	Formal  BYS59A	0 = No 1 = Yes
		Has gone to counselor for college entrance information	

(continued)

### Appendix A (continued)

Variable	Scale	ELS:2002 Variable and Description		ELS Coding
		BYS59B	Has gone to teacher for college entrance information	0 = No 1 = Yes
		BYS59C	Has gone to coach for college entrance information	
		BYS59I	Has gone to college representative for college entrance information	
		Informal		
		BYS59D	Has gone to parent for college entrance information	
		BYS59E	Has gone to friend for college entrance information	
		BYS59F	Has gone to sibling for college entrance information	
		BYS59G	Has gone to other relative for college entrance information	
Postsecondary investment (psinv)	0 = No investment (response of 1 or 2) 1 = College enrollment (response of 3 or 4) 2 = 4-year college completion or higher (student response of 5,6, or 7)	BYSTEXP	How far in school students will get	1 = Less than high school 2 = High school grad or GED 3 = Attend or complete 2 year 4 = Attend but not finish 4 year 5 = Graduate from college 6 = Obtain master's degree 7 = Obtain advanced degree
Academic initiative variables				
Academic flow (flow)	0 = No flow experiences 1 = Flow in math or reading 2 = Flow in math and reading (student self-report)	BYS87A	Gets totally absorbed in mathematics	1 = Strongly agree 2 = Agree
		BYS87E	Gets totally absorbed in reading	3 = Disagree 4 = Strongly disagree
Academic enjoyment (enjoy)	0 = No academic enjoyment 1 = Enjoys math or reading 2 = Enjoys math and reading (student self-report)	BYS87B	Thinks reading is fun	1 = Strongly agree 2 = Agree
		BYS87C	Thinks math is fun	3 = Disagree 4 = Strongly disagree
Academic initiative (init)	0 = No academic initiative 1 = Academic initiative (student response of 1 or 2)	BYS27A	Classes are interesting and challenging	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Academic investment variables				
Academic efficacy (aceff)	0 = No academic efficacy 1 = Academic efficacy (student response of 1 or 2)	BYS89E	Can learn something really hard	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree

(continued)

### Appendix A (continued)

Variable	Scale	ELS:2002 Variable and Description		ELS Coding
Academic persistence (pers)	0 = No academic persistence 1 = Academic persistence (student response of 1 or 2)	BYS89O	Keeps studying even if material is difficult	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Academic effort (try)	0 = No academic effort 1 = Academic effort (student response of 1 or 2)	BYS89V	Puts forth best effort when studying	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Academic attention (atten)	0 = No academic attention 1 = Academic attention (teacher response of 4 or 5)	BYTE16	How often is student attentive in class?	1 = Never 2 = Rarely 3 = Some of the time 4 = Most of the time 5 = All of the time
Academic investment (acinv)	0 = Not important 1 = Academic investment (student response of 3)	BYS37	Importance of good grades to student	1 = Not important 2 = Somewhat important 3 = Important
School investment variables				
School social investment (schsoc)	0 = Little or no investment 1 = Investment (student response of 1 or 2)	BYS27E	School is a place to meet friends	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Civic investment (civinv)	0 = Little or no investment 1 = Civic investment (student response of 3 or 4)	BYS54F	Importance of helping others in community	1 = Not important 2 = Somewhat important 3 = Important 4 = Very important
Occupational investment (ocinv)	0 = Little or no investment 1 = Investment (student response of 3)	BYS54A	Importance of being successful in line of work	1 = Not important 2 = Somewhat important 3 = Very important
Postsecondary investment (psin)	0 = No investment (student response of 1 or 2) 1 = College enrollment (student response of 3 or 4) 2 = 4-year college completion or higher (student response of 5,6, or 7)	BYSTEXP	How far in school students will get	1 = Less than high school 2 = High school grad or GED 3 = Attend or complete 2 year 4 = Attend but not finish 4 year 5 = Graduate from college 6 = Obtain master's degree 7 = Obtain advanced degree
School investment variables				
School social investment (socinv)	0 = Little or no investment 1 = Investment (student response of 1 or 2)	BYS27E	School is a place to meet friends	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Occupational investment (ocinv)	0 = Little or no investment 1 = Investment (student response of 3)	BYS54A	Importance of being successful in line of work	1 = Not important 2 = Somewhat important 3 = Very important
Civic investment (civinv)	0 = Little or no investment 1 = Civic investment (student response of 3 or 4)	BYS54F	Importance of helping others in community	1 = Not Important 2 = Somewhat important 3 = Important 4 = Very important

(continued)

## Appendix A (continued)

Variable	Scale	ELS:2002 Variable and Description	ELS Coding
<b>Ambivalence variables</b>			
General ambivalence (amb)	0 = No ambivalence 1 = Generally ambivalent (2 or more ambivalent responses) (student self-report)	(Sum of affirmative responses / 4) BYS38 "Somewhat likes school" or "doesn't know" BYSTUEX "Doesn't know" how far they'll get in school BYS54A "Somewhat important to be successful in work" BYS54O "Somewhat important to get good education"	"Somewhat agrees" or "unsure/don't know"
School ambivalence (schamb)	0 = No ambivalence 1 = Ambivalent (student response of 1 or 2)	BYS27C Has nothing better to do than school For Peer Review	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
<b>Dis-identification variables</b>			
Teacher alienation (talien)	0 = No alienation experience 1 = Experienced alienation (student response of 1 or 2)	BYS20H In class often feels put down by teacher	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
Peer alienation (palien)	0 = No alienation experience 1 = Experienced alienation (student response of 1 or 2)	BYS20I In class often feels put down by students	1 = Strongly agree 2 = Agree 3 = Disagree 4 = Strongly disagree
School dis-identification (schdis)	0 = Does not disidentify 1 = Disidentifies (student response of 1)	BYS28 How much likes school	1 = Not at all 2 = Somewhat 3 = A great deal

*Note.* ELS = Educational Longitudinal Study.

## Appendix B

### *Variable Names and Codes for Indicators of Behavioral Profile Membership*

Variable	Scale	ELS:2002 Variable and Description	ELS Coding
<b>Indicators of engagement in school-sponsored ECAs</b>			
Structured interscholastic sports (sports)	0 = Did not participate 1 = Participated in at least one	BYBASEBL Baseball BYSOFTBL Softball BYBSKTBL Basketball BYFOOTBL Football BYSOCER Soccer BYTEAMSP Other team sport BYSOLOSP Individual sport BYCHRDRL Cheerleading or drill team	1 = No interscholastic team 2 = Did not participate 3 = Participated in JV 4 = Participated in varsity 5 = Varsity captain
Unstructured school sports (intramural)	0 = Did not participate 1 = Participated in at least one	BYS39A Baseball BYS39B Softball BYS39C Basketball BYS39D Football BYS39E Soccer BYS39F Other team sport BYS39G Individual sport BYS39H Cheerleading or drill team	1 = No intramural team 2 = No (did not participate) 3 = Yes (did participate)

*(continued)*

## Appendix B (continued)

Variable	Scale	ELS:2002 Variable and Description		ELS Coding
School arts (arts)	Music or Drama	BYS41A	Participated in school band or chorus	0 = No
	0 = Did not participate 1 = Participated in at least one	BYS41B	Participated in school play or musical	1 = Yes
School service (service)	0 = Did not participate	BYS 41E	Participated in school yearbook or newspaper	0 = No
	1 = Participated in at least one	BYS 41F	Participated in school service clubs	1 = Yes
		BYS41H	Participated in school hobby clubs	
		BYS41C	Participated in student government	
Indicators of engagement in school-sponsored ECAs (student self-reports)				
School-sponsored vocational club (vocclub)	0 = Did not participate	BYS41I	Participated in school vocational clubs	1 = Yes
	1 = Participated in at least one	BYS71A	Participated in cooperative education	0 = No
		BYS71B	Participated in internship	
		BYS71C	Participated in job shadowing	
		BYS71F	Participated in school-based enterprise	
School academic club (saclub)	0 = Did not participate	BYS41D	Participated in academic honor society	0 = No
	1 = Participated in at least one	BYS41G	Participated in school academic clubs	1 = Yes -1 = Don't know
Community service (comserv)	0 = Did not participate 1 = Participated	BYS71E	Participated in community service	0 = No 1 = Yes
Indicators of activity intensity (student self-reports)				
School-based extracurricular activity intensity (ecin)	0 = None	BYS42	Hours spent each week on school-sponsored extracurricular activity	0 = 0 hours
	1 = 1–2 hours of participation each day			1 = 1 hour
	2 = 2 or more hours of participation each day			2 = 2 hours
				3 = 3 hours
Out-of-school time extracurricular activity intensity (ost_in)	0 = No activity	BYS44F	How often takes music, arts, or language classes	4 = 4 hours
	1 = Participates less than two times per week	BYS44G	How often takes sports lessons	1 = Rarely or never
	2 = Participates two or more times per week	BYS44H	How often plays non-school sports	2 = Less than once a week
				3 = Once or twice weekly
Unstructured out-of-school time (tv_vid)	0 = 1 or less hours per day	BYS 48A	Hours/day spent watching TV on weekdays	4 = Everyday or almost
	1 = More than 1 but less than 4 hours per day	BYS49A	Hours/day playing video or computer games on weekdays	0 = 0 hours
	2 = 4 or more hours per day			1 = 1 hour
				2 = 2 hours
				3 = 3 hours
				4 = 4 hours
Homework (hw)	0 = None	BYS34B	Hours/week spent on homework in and out of school	5 = 5 hours
	1 = 1–2 hours daily			6 = 6 or more hours
	2 = More than 2 hours daily			0 = 0 hours
				1 = 1 hour
				2 = 2 hours
				3 = 3 hours

(continued)

## Appendix B (continued)

Variable	Scale	ELS:2002 Variable and Description		ELS Coding
Out-of-school time reading (read)	(Per week) 0 = Less than hour per day 1 = 1 or more hours per day	BYS43	Hours/week spent reading outside of school (non-school reading)	0 = 0 hours 1 = 1 hour 2 = 2 hours 3 = 3 hours 4 = 4 hours
Indicators of student conduct (student self-reports)				
Student class cutting (cut)	0 = None 1 = One to two times 2 = Three or more times	BYS24B	How many times cut/skipped classes	1 = Never 2 = One to two 3 = Three to six 4 = Seven to nine 5 = Ten or more
Student absences (abs)	(For the current quarter) 0 = Two or less absences 1 = Three to six 2 = Seven or more	BYS24C	How many times absent from school	1 = Never 2 = One to two 3 = Three to six 4 = Seven to nine 5 = Ten or more
Suspensions (susp)	(For the current quarter) 0 = None 1 = Once or twice 2 = Three or more	BYS24E	How many times put on in-school suspension	1 = Never 2 = One to two 3 = Three to six 4 = Seven to nine 5 = Ten or more
		BYS24F	How many times suspended/put on probation	

*Note.* ELS = Educational Longitudinal Study; ECA = extracurricular activity; JV = junior varsity.

## Appendix C

### *Estimating the Unconditional Latent Class Measurement Models and Latent Class Regressions*

This technical appendix details our analytic approach for each of the primary latent class models estimated in this article, represented by path diagrams in Figures C1 and C2. We begin with a more detailed discussion of the latent class enumeration procedure used to evaluate our behavioral engagement profile models. Then, we describe the strategies used to estimate our latent class regression models.

As described in the narrative, the process of determining the “best-fitting” latent class analysis (LCA) was an exploratory process in this study because there were no a priori assumptions about the number or nature of latent classes in the data. Using Mplus Version 7.3 (Muthén & Muthén, 2014), we fit our LCA models in a progression of iterative steps. We started first by estimating a one-class solution, assuming no relationships between any of the latent class indicators. We then successively added classes until the resultant model was not well identified as indicated by one or more of the following occurrences: lack of model convergence, lack of replication of the best log likelihood value across random sets of start values, condition number less than  $10^{-6}$ , and/or the extraction of a small and/or

untenable latent class—indicating a possible overextraction of classes.

We estimated our LCA models using full-information maximum likelihood (FIML) via the EM algorithm. Further, since latent class models are notorious for converging to local rather than global optima (during maximum likelihood estimation), we utilized the “random start values” perturbation facility in Mplus in order to try to replicate the optimum solution across multiple sets of start values for each model. This was done to increase confidence that, given the observed data, the returned solution was the global maximum of the likelihood function (Masyn, 2013). In all estimated models, we accounted for nonindependence of student observations (i.e., students are nested within schools) by adjusting our standard errors for clustering within schools (with clusters identified by the school ID variable) using the sandwich estimator available in Mplus’s “type=complex” command.

We used a combination of statistical indicators and substantive interpretation to determine the “best” number of latent classes, yielding a well-fitting, parsimonious, and interpretable model (Masyn, 2013; Nylund, 2007; Van Horn et al., 2008). We evaluated each LCA in relation to other models, using the three fit indices for LCA that are preferred for evaluating these models: the Bayesian information criterion (BIC), the consistent Akaike information criterion (CAIC), and the

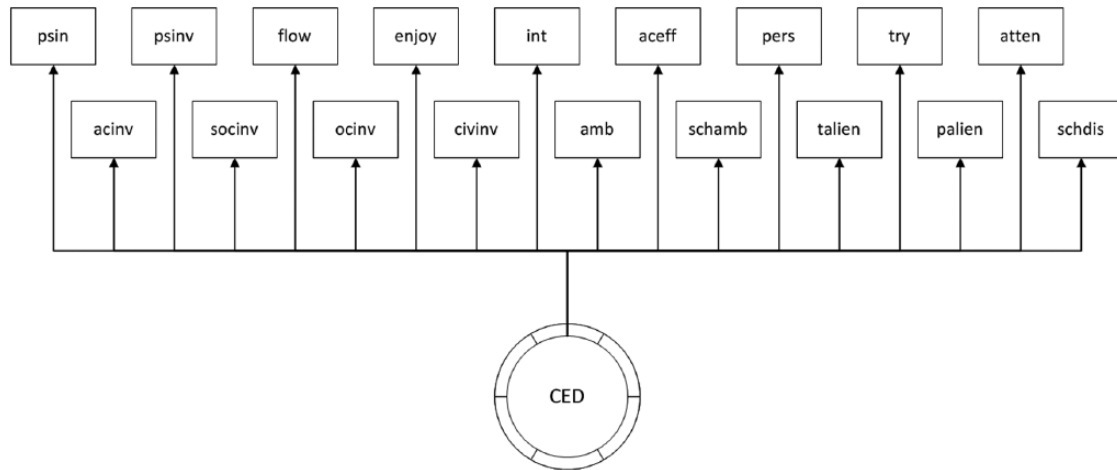


FIGURE C1. *Path diagram of latent class measurement model for student engagement disposition profiles.*

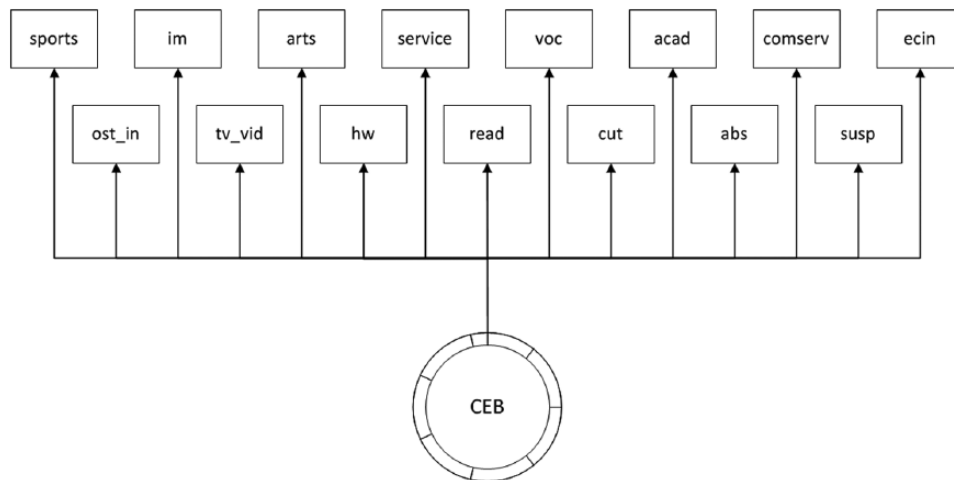


FIGURE C2. *Path diagram of latent class measurement model for student engagement behavioral profiles.*

approximate weight of evidence criterion (AWE). In each case, the model with the smallest value on the index is judged as best among the models under consideration (Masyn, 2013). In situations for which the smallest value corresponds to the model with the largest number of classes that is still well identified, we also examined plots of the BIC, CAIC, and AWE values versus the number of classes to identify “elbow” joints. This evaluation is analogous to the use of a scree plot in exploratory factor analysis.

In addition to the BIC, CAIC, and AWE, we evaluated our models using the adjusted Lo-Mendell-Rubin likelihood ratio test (LMR-LRT), as the bootstrap likelihood ratio test (BLRT) is not available for clustered, survey designs, such as the Educational Longitudinal Study (ELS). The LMR-LRT provides a  $p$  value for a  $K$ -class model versus a  $(K + 1)$ -class model with the first nonsignificant  $p$  value indicating a lack

of statistically significant improvement in model fit adding another class in the enumeration.

Finally, because our intent was to extract substantively meaningful and distinct classes, we also evaluated class separation and homogeneity (giving preference to solutions with large between-class differences and small within-class variability) and, relatedly, classification diagnostics, including entropy, average posterior class probabilities, and modal class assignment proportions. Here, the more precise classification of individuals in the sample reflected greater class separation and better discriminant validity of class membership (Masyn, 2013).

*Model Validation.* Since the LCA approach used in this study is data driven and, therefore, sample dependent, the latent class solutions culled from our analyses may conflate sampling error

with “true” population heterogeneity. Therefore, in order to empirically validate our profiles of students’ behavioral engagement, we performed a split-half cross-validation procedure using two random subsamples generated from the larger ELS:2002 data set (Van Horn et al., 2008). We used the first sample (Sample A) as a calibration sample, conducting initial, exploratory latent class enumeration for the behavioral profiles. Next, we fitted a smaller set of LCA models to the validation sample (Sample B) with the number of classes based on the top-fitting models from the enumeration on Sample A. We then compared the class proportions and class-specific item probabilities for each solution culled from the validation sample to the findings yielded from the calibration sample. The model with class profiles that were “best replicated” across both samples was selected as the “optimal” latent class solution.

#### *Estimating Latent Class Regression Models*

Although the FIML estimators included in Mplus 7.3 allow for missingness on endogenous indicators of behavioral profile membership under the missing-at-random (MAR) assumption, Mplus will listwise delete any case with incomplete data on exogenous covariates. Consequently, in order to circumvent this listwise deletion default for our predictor variables, we used a multiple imputation approach.

Here, using the Bayes estimator in Mplus 7.3 (Muthén & Muthén, 2010), we imputed 10 data sets with complete covariate data. We also ran our final latent class model with the Bayes estimator, using the FIML parameter estimates as start values to obtain *plausible* latent class values for each individual in the sample, in essence, multiply imputing latent class membership for each participant. We then followed the procedures documented in our study of student engagement dispositions (M. Lawson & Masyn, 2015) and estimated a multinomial logistic regression model of behavioral profile membership on student ethnicity, gender, ninth-grade GPA, and socioeconomic status. For these conditional analyses, the results were averaged across 10 imputed data sets of covariates and latent class membership, with standard error adjustments done automatically in the “type=imputation” facility of Mplus 7.3.

*Determining Regression Model Fit and Statistical Significance.* When multinomial logistic regression techniques are located within the setting of mixture models with multiple imputed data sets, there are limited options for determining model fit (Nylund, 2007). Specifically, whereas conventional structural equation models rely on a set of common fit indices (e.g., root mean square error of approximation, comparative fit index, non-normed fit index), these indices do not apply to latent class regression modeling. Consequently, we evaluated the best relative fit of our multinomial latent class regression models by way of a simple likelihood ratio test.

In addition to issues of overall model fit, the direct interpretation of multinomial logistic regression model parameters does

more to obscure than illuminate the relationships between predictors and multinomial outcome, as the resultant slope coefficients are conditional log odds ratios for membership in one class versus the reference class, conditional on membership in one of the two classes corresponding to a one-unit difference in the predictor. Additionally, the statistical significance of each coefficient does not provide an overall test of association between the predictor and the multinomial outcome. This obfuscation is especially pronounced in studies, like this one, where our multinomial variables lack a logical (or practically meaningful) reference category. Moreover, because each latent class regression model includes a multinomial outcome variable with several outcome categories, the process of interpreting multiple, pairwise comparisons (e.g., Category 1 vs. 2, Class 1 vs. 3, Category 1 vs. 4, and so forth) can quickly become unwieldy.

For this reason, two steps were taken to help readers better understand the meaning and significance of the study’s latent class regression models. First, in order to avoid the need to report a host of pairwise comparisons between multinomial predictors and outcomes, we present model-estimated behavioral profile membership probabilities for critical values of the covariates, based on the estimated multinomial regression coefficients generated from Mplus 7.3, rather than individual coefficients (i.e., conditional log odds ratios). As a consequence of this effort, readers are able to examine directly the differences in the *overall latent class distribution* at those different covariate values.

Second, just as it is difficult to interpret the meaning of several pairwise comparisons in a multinomial logistic regression model, it can also be difficult to evaluate whether the predictors have an overall effect on the distribution of the multinomial outcome. Therefore, in order to examine associations between our predictor variables and behavioral class membership, we conducted global hypothesis tests for each predictor variable using a multivariate Wald test executed through the “model test” command in Mplus. Essentially, each of these global hypothesis tests evaluates simultaneously whether all of the multinomial logistic regression coefficients associated with a particular predictor are equal to zero. This null hypothesis corresponds to “no association” between the predictor and the multinomial outcome, controlling for all other predictors. Thus, a significant *p* value translates to statistically significant evidence of an adjusted association between the given predictor and latent class membership. These statistics can be located in Table 4 in the narrative, which depicts the results of our latent class regression models.

## **Appendix D**

### *Analyzing the Association Between Latent Classes of Engagement Behaviors and Dispositions*

In order to examine the intersection of student disposition profiles and student behavioral profiles, we needed to

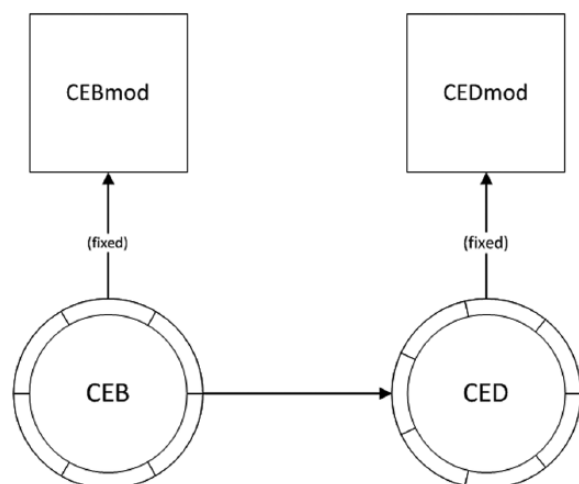


FIGURE D1. Path diagram of the Step 3 latent class association model.

estimate the association between the latent class variable representing engagement dispositions and the latent class variable representing engagement behaviors. In a conventional “one-step method,” we would combine and simultaneously estimate the latent class measurement models for each of the latent class variables, with all respective indicators (18 for the disposition profiles and 15 for the behavioral profiles), along with estimating the (structure) association between the two latent variables. This model is computationally unwieldy given the number of parameters being estimated, and any misspecification with regards to the relationship between the two sets of observed latent class indicators can lead to biased estimates of the latent class variable association and can lead to shifts in the meaning of each latent class variable. For example, the disposition indicators could alter the structure and meaning of the behavioral latent classes and vice versa.

A “three-step method,” explored by Vermunt (2010) for latent class regression and further evaluated by Asparouhov and Muthén (2014) for latent class outcomes, avoids these drawbacks. This three-step approach also avoids the drawbacks of the “classify-analyze” approach in which individuals are classified into their most likely latent classes and then these class assignments are treated as known group membership (i.e., treated as an observed, perfectly measured multinomial variable) in subsequent analyses. Such an approach ignores classification error and can lead to biased estimates of associations with class membership.

In Step 1 of the manual three-step process in Mplus, we estimated each latent class measurement model for each latent class variable separately (as described in Appendix C). Let CED be the latent class variable for engagement dispositions and let CEB be the latent class variable for engagement behaviors. In Step 2, a modal class assignment variable was created for each latent class variable, called CEDmod and

CEBmod. CEDmod was a six-category multinomial variable with the value for each individual in the sample corresponding to the number of the CED class to which the individual was most likely to belong, given his or her observed disposition indicator values and the estimated CED model, as determined by the posterior latent class probabilities. Similarly, CEBmod was a seven-category multinomial variable with the value for each individual in the sample corresponding to the number of the CEB class to which the individual was most likely to belong based on his or her posterior CEB class probabilities. In this second step, uncertainty rates for the modal class assignments are also calculated based on the posterior class probabilities and model estimates. In Step 3, represented by a path diagram in Figure D1, CEBmod and CEDmod are used as single multinomial indicators of CEB and CED, respectively, with the parameters defining the relationship between the CEBmod indicator and CEB fixed at values that reflect the uncertainty rates computed in Step 2. In this way, the measurement errors in CEBmod and CEDmod are taken into account. The parameters related to the association between CED and CEB are estimated—in this case, the association was specified as a multinomial regression of CED on CEB, although equivalent parameterizations were also fit using a multinomial regression of CEB on CED and a nondirectional association specification.

Although this manual three-step process is designed to account for the measurement error in class assignment while maintaining the integrity of the latent class formation from Step 1, there is no guarantee that class membership is consistent from Step 1 to Step 3. Thus, we also confirmed, comparing estimated latent class proportions and modal latent class assignment from Step 1 to Step 3, that the latent class formation was, indeed, stable across the first and third steps.

## Appendix E

### *Estimating the Higher-Order Latent Class Measurement Model*

Following the same process as the three-step model, described in Appendix D, to examine the relationship between latent class profiles of engagement dispositions and behaviors, we specified a higher-order latent class measurement model in Step 3, using the latent class variables, CED and CEB, as indicators of a higher-order latent class variable, CSE, to reduce the 42 ( $6 \times 7$ ) possible disposition-by-behavior latent class profiles into a smaller number of (higher-order) latent classes defined by the dominant patterns of socioecological engagement across disposition and behavioral profiles (see Figure E1). The classes of CSE were characterized by class-specific probabilities for each of the latent disposition profiles and each of the latent behavioral profiles.

The enumeration process for the higher-order latent class variable was similar to the latent class enumeration process

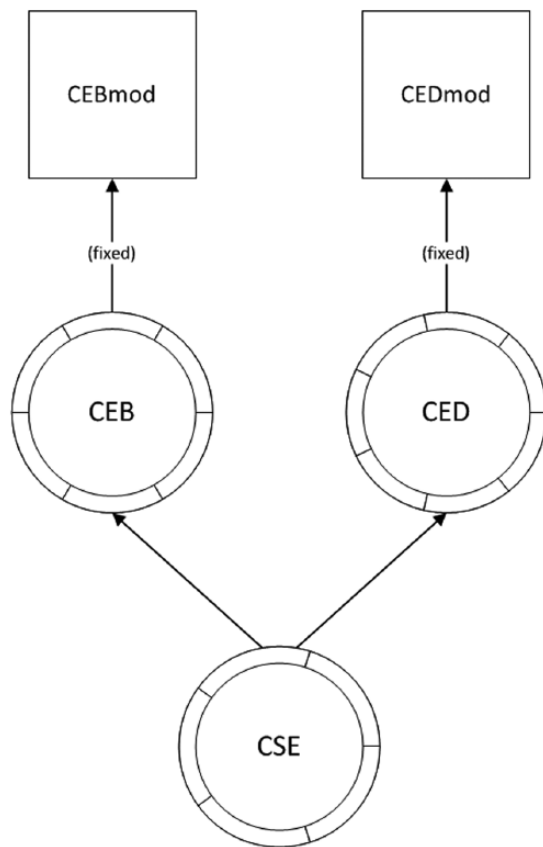


FIGURE E1. Path diagram of the higher-order latent class measurement model.

described in Appendix C. However, with only 41 degrees of freedom for the higher-order latent class measurement model, any model with more than three classes for CSE was underidentified and required some class-specific disposition and behavioral profiles probabilities to be fixed at either 1 or 0. The placements of those identifying constraints were not decided a priori but instead were determined during model estimation.

The LMR-LRT statistic is not available for higher-order latent class models, but we could compute the CAIC, BIC, and AWE. For evaluation of overall fit, we used the final three-step association model, from Appendix D, as the absolute best-fit threshold. The three-step model, allowing CED and CEB to freely associate, perfectly reproduces the 42 latent response patterns across CED and CEB. Any enumeration of CES that was significantly under that threshold, in terms of the log likelihood value, was considered poor fitting. The best-fit threshold was met by the six-class model; thus, no better fit to the CED-CEB intersection could be achieved beyond six classes for CES. The higher-order latent class models with fewer than four CES classes were deemed to have inadequate fit according to this criterion even though the three-class CES model had the lowest CAIC and AWE values (comparing

one- to six-class models for CES). The four-class CES model had the lowest BIC value, while the five-class CES model yielded a log likelihood much closer to the best-fit threshold. The four-, five-, and six-class CES model solutions were all evaluated for separation, homogeneity, and substantively interpretability of the resultant classes. The five-class CES model was selected as the final model, as we found it superior to the four- and six-class models when weighing both statistical and substantive considerations.

### Acknowledgments

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### Notes

1. Consistent with National Center for Education Statistics policies and procedures, the number of students and schools included in our sample was rounded to the nearest ten.
2. This study was designed to treat profiles of students' activity and dispositional engagement as interrelated components of a global social-ecological measure of the student engagement construct. For this reason, no covariates were entered in our disposition on behavioral profile regression models. Covariates were eschewed in this specification because just as it is inappropriate to adjust for covariates when developing a confirmatory or exploratory measurement model (for continuous variables), it is inappropriate to adjust for those factors when the measurement model is constituted by categorical latent variables.

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