Abstract

In Hawaiʻi, approximately one in ten students enrolled in a public high school at the start of their ninth-grade year transfer to another school at least once. Previous research suggests that student mobility can adversely affect student learning and increase the risk of students dropping out. Students who are mobile become disengaged with school and fail to graduate on time. This study examined the relationship between student mobility and graduation outcomes to determine if further attention to student mobility in Hawaiʻi is warranted.

To examine the impact of student mobility on graduation outcomes, this study incorporated a cross-classified multiple-membership model. Previous studies either removed the mobile students from their model or included the school-level predictors of only one school to determine the impact of student mobility, failing to recognize that a student’s experience in all schools attended affect the student’s disposition towards education. The multiple-membership approach allowed for the inclusion of predictors of each school in which a mobile student was enrolled as one weighted data point for each school-level predictor to provide more accurate estimates of multiple school effects on student on-time graduation.

The utilization of the cross-classified multiple-membership model provided a better understanding of how student mobility, which leads to multiple configurations of students within schools, impacts graduation outcomes. The results of this study revealed that student mobility did significantly impact graduation outcomes across Hawaiʻi’s public high schools, decreasing a student’s odds of graduating on time. Thus, to increase graduation rates across the state, the appropriate supports and services must be provided for mobile students to facilitate student success.
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<table>
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<th>Description</th>
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<tr>
<td>ACGR</td>
<td>Adjusted cohort graduation rate</td>
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<tr>
<td>GPA</td>
<td>Grade point average</td>
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<td>HIDOE</td>
<td>Hawai‘i State Department of Education</td>
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Chapter 1. Conceptualization of the Research Problem

Student mobility has been identified as a hindrance to student success in school. Numerous studies have indicated that student mobility can negatively impact student behavior, test scores, grades, promotion, and graduation (Rumberger, 2003; Rumberger & Larson, 1998; Swanson & Schneider, 1999). Changing schools “can harm normal child and adolescent development by disrupting relationships with peers and teachers as well as altering a student’s educational program” (Rumberger, 2015, p. 10). Students who move from school to school are affected academically, socially, and psychologically. Unfortunately, student mobility is common across the United States, especially for elementary school students. According to Rumberger (2003), “[Mobility] is the norm during elementary school, while it is the exception during high school” (p. 7). Regardless of the students’ age, the effects of student mobility ultimately impact graduation outcomes.

Student mobility may be family-initiated or school-initiated. Student mobility is often viewed as an inevitable result of residential mobility for which schools can do little about (Rumberger & Larson, 1998). Residential mobility is initiated by families who move from one residence to another due to reasons that are voluntary, such as employment or a better home, or involuntary, such as losing their home or a divorce (Rumberger, 2003; Rumberger, 2015; Swanson & Schneider, 1999). Socioeconomic status (SES) plays a significant role in mobility. School and residential mobility are higher among students of lower SES than those of higher SES (Rumberger & Larson, 1998). Student mobility has “negative effects on school performance, which suggests that the low SES students are disadvantaged, in part, because they are more likely to change schools and more likely to change residences than high SES students”
(Rumberger & Larson, 1998, p. 20). Thus, while students are already at a disadvantage due to their socioeconomic status, mobility widens the achievement gap.

Schools also play a role in student mobility. Parents may elect to transfer their child from one school to another due to the school’s curricular, co-curricular, or extracurricular programs or for the safety and well-being of the child. Policymakers and education administrators may also initiate a change in schools through school closure, redrawn district lines, or expulsion (Rumberger, 2003; Rumberger, 2015). Whether student mobility is family-initiated or school-initiated, the impact on student success can be detrimental.

Student mobility has a strong impact on high school graduation. Students who make at least one non-promotional school change (i.e., a transfer not due to promotion to middle or high school) during their educational careers are less likely to graduate on time. When this non-promotional school change takes place during high school, the likelihood to graduate on time is even less. Rumberger (2003) noted there is “overwhelming evidence that student mobility during high school diminishes the prospects of graduation” (p. 10). Students who transferred from one school to another at least once during high school were more likely to drop out or enroll in an alternative educational program than students who are stable (Grim, 2019; Haveman, Wolfe, & Spaulding, 1991; Rumberger & Larson, 1998). Students who are mobile are less likely to earn a regular high school diploma and the more times students change schools during high school, the likelihood of these students dropping out or enrolling in an alternative educational program increases. The increase in the risk of not completing high school is greater for students who are mobile even after accounting for other risk factors that may affect graduation outcomes, such as lower family income, lower academic achievement, behavioral problems, and higher absentee
rate (Gasper, DeLuca, & Estacion, 2012). Moving “upward” to a better school in a better neighborhood did not mitigate the risks of dropping out (Metzger, Fowler, Anderson, & Lindsay, 2015). Interestingly, students who change schools during the first two years of high school are more likely to drop out of school than students who are stable. However, if these mobile students persist through tenth grade, the likelihood of dropping out significantly decreases (Swanson & Schneider, 1999). Students who are mobile during the early years of high school are more likely to graduate with a regular high school diploma if they do not drop out within the first two years.

Student mobility not only impacts student success, but also impacts school performance. The disruption caused by student turnover can adversely affect the students who remain in the school. Rumberger (2015) found that non-mobile students enrolled in a high school with a high student mobility rate have significantly lower average test scores and struggle academically. Another study indicated that students who attend a school with higher student mobility rates experience a higher risk of dropping out (South, Haynie, & Bose, 2007). Teachers in schools with high student mobility continuously adjust their classroom instruction when students move in and out of their classes. This, in turn, disrupts the learning of the non-mobile students. Thus, student mobility during high school not only affects the graduation outcome of mobile students, but also that of non-mobile students.

**Purpose**

Student transition in Hawai‘i’s public schools is a priority for the Hawai‘i State Department of Education (HIDOE). Most students make two planned school changes during their K-12 education – from elementary school to middle or intermediate school and from middle or intermediate school to high school. Although supports and resources are often provided for
students who transition from one school level to the next (i.e., middle school to high school),
these are often not provided for students who transfer from school to school within the same
school level (i.e., one high school to another high school). In one large study of mobility and
achievement in Great Britain, Leckie (2009) found students who made promotional school
moves made similar progress to pupils who remained in the same school throughout their
secondary schooling; however, students who changed schools for non-promotional reasons made
significantly less progress than stable students. Given documented challenges to student
performance and success associated with mobility, this study will examine whether the effects of
student mobility during high school warrants attention in Hawai‘i. Are student outcomes
different for students who transfer at least once during high school than they are for students who
remain in the same school from the first day as a true freshman through graduation? Does student
mobility in high school negatively impact on-time graduation, delaying graduation or leading
students to either drop out or enroll in an alternative education program? How do students’
background and school demographics moderate the relationship between student mobility and
the probability of graduating?

Gaining a better understanding of the effects of student mobility will help high school
personnel to provide the proper academic and social supports for students who move from school
to school, which should, in turn, lead to greater student success. To investigate on-time
graduation, this study incorporates a relatively underused approach – a cross-classified multiple-
membership modeling – to appropriately examine the issue of student mobility in studies of high
school students’ graduation outcomes. In estimating students’ likelihood to graduate on time, it
seems intuitive to recognize the effect that every school has on that outcome (Leckie & Owen,
These are important years in children’s educational careers; thus, it is necessary to incorporate student mobility to ensure accurate estimates for a clearer picture of its impact on graduation outcomes.

**Background of the Study**

HIDOE has approximately 51,000 students enrolled in grades 9 through 12 each year.\(^1\) Of these high school students, approximately six percent are retained and four percent drop out of school each year.\(^2\) Overall, approximately 14 percent of the state public school graduation cohort drop out of high school, with more than 75 percent of the state’s public high schools having a dropout rate of at least 10 percent and more than 35 percent having a dropout rate of at least 20 percent.\(^3\) According to the U.S. Census, people who do not have a high school diploma will make $10,000 less than people with a high school diploma and $40,000 less than people who earn a bachelor’s degree.\(^4\) If HIDOE plans to meet its goal of all students being able to “demonstrate they are on a path toward success in college, career, and citizenship,”\(^5\) HIDOE must increase its graduation rate. To increase the graduation rate, educators need to understand why students are failing to graduate from high school.

Beginning with School Year 2010-11, HIDOE has calculated its graduation rate using the four-year adjusted cohort graduation rate methodology\(^6\) as required by the United States

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\(^2\) Data received from the Hawai‘i State Department of Education Accountability Section. http://arch.k12.hi.us/school/trends/trends.html#


\(^5\) https://www2.ed.gov/policy/elsec/guid/hsgrguidance.pdf
Department of Education. The four-year adjusted cohort graduation rate (ACGR) is the percentage of students who graduate with a regular high school diploma within four years. The ACGR methodology identifies the denominator as the number of students who form the original cohort of first-time students in grade 9 enrolled in high school on the HIDOE Official Enrollment Count date, the tenth student day of the school year. The denominator is adjusted by adding the students who enroll in high school and join the cohort and subtracting the students who leave the cohort by transferring to another school outside HIDOE or to a detention facility, exiting the HIDOE system to be homeschooled, or moving to another country and students who are deceased. The numerator is defined as the number of students in the cohort who earned a regular high school diploma before, during, or at the conclusion of the fourth year of high school or the summer session immediately following the fourth year. HIDOE does not include students who receive a certificate through the special education program in the numerator of its graduation rate; these students are, however, included in the denominator.

According to the National Center for Education Statistics, the national ACGR for public high schools was 83.2 percent in 2014-15. Hawai‘i’s ACGR of 81.6 percent was lower than the national ACGR and lower than 32 of the 50 states and Washington, D.C. To increase schools’ graduation rate and reach the state goal of a graduation rate of 90 percent by 2025, HIDOE personnel must provide the necessary supports and services to ensure students graduate on time and to decrease the public high school dropout rate.

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Need and Significance of the Study

Previous research has found that students’ likelihood of graduating is affected by their educational experiences prior to high school and is related to their economic and demographic backgrounds (e.g., Alexander, Entwisle, & Kabbani, 2001; Allensworth & Easton, 2007; Heck & Mahoe, 2006; Neild & Balfanz, 2006; Rumberger, 2004). The manner in which many schools are constituted (course scheduling, teacher assignment, discipline procedures) reproduce inequities that exist in the surrounding economic, social, and political milieu (Pollock, 2004; Watts & Erevelles, 2004). Researchers identified features of schools (i.e., tracking and course-taking, student-teacher relationships, conduct policies and procedures) that may socially organize leaving school early for some groups of students (Friedkin & Thomas, 1997; Mehan, 1997; Oakes, 1985). Leaving school early is neither exclusively a problem of individual students who disengage in their courses nor of school social reproduction (Mehan, 1997).

Recognizing that a successful transition into high school is critical in ensuring students graduate, HIDOE has made student transition one of its priorities in the Hawai‘i State Department of Education and Board of Education Strategic Plan, 2017-2020.8 HIDOE personnel believe students “who feel connected to school are more likely to engage and learn.”9 Understanding that transitions from one school to another “can disrupt [students’] sense of connectedness to school,”10 HIDOE proposes to better support students through their transitions through school practices, counseling, and innovative school experiences. As a statewide student

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8 http://www.hawaiipublicschools.org/DOE%20Forms/Advancing%20Education/SP2017-20.pdf
9 Hawai‘i State Department of Education and Board of Education Strategic Plan, 2017-2020, p. 8.
10 Hawai‘i Department of Education and Board of Education Strategic Plan, 2017-2020, p. 8.
success indicator and a Strive HI School Performance Report\(^{11}\) indicator, HIDOE measures the on-time promotion rate of ninth graders, the percentage of ninth graders who are promoted to grade 10 on time. This on-time promotion rate implies a successful transition from middle school to high school.

To be most effective, school leaders and staff need to understand more thoroughly how students lose their sense of connectedness with their school and what leads these students to eventually drop out of school. The HIDOE definition of student dropout is a student who either stops attending school or exits a HIDOE school to enroll in an alternative education program. Of the 2015 graduation cohort, 14.0 percent dropped out of school.\(^{12}\) Dropout rates are often attributed to student demographics, such as socioeconomic status, race and ethnicity, and student academic or social performance (Rumberger & Palardy, 2005; Goldschmidt & Wang, 1999; Rumberger & Thomas, 2000). What may be overlooked as a contributing factor to students dropping out of school, however, is student mobility. Students may move between schools for a variety of reasons, including change of residence, change of employment of parent, a geographic exception to a more appropriate school, school closure, and administrative disciplinary action (Grigg, 2012; Ihrke & Faber, 2012; Lee, 2019; Rumberger, 2015). Although most research indicates that mobility generally has a negative impact on graduation status, mobility for some students may be beneficial if the reason and timing represent a “strategic” move to a better educational placement (Rumberger, 2015). This study will identify the effects of student mobility on the graduation outcomes of Hawai‘i’s public school students.

\(^{11}\)https://www.hawaiipublicschools.org/VisionForSuccess/AdvancingEducation/StriveHIPerformanceSystem/Pages/home.aspx

Challenges in Incorporating Student Mobility

Unfortunately, student mobility is common among high school students and can adversely affect academic learning due to the disruption of school-based social ties and academic routines. In general, the negative effects of school mobility increase with the number of school moves (e.g., Gasper et al., 2012; Heck & Mahoe, 2006; Leckie, 2009; Xu, Hannaway, & D’Souza, 2009). Estimating the effects of mobility, however, is problematic because, even without mobility, family issues as well as challenges experienced at school may lead to poor outcomes for mobile students (Rumberger, 2003; 2015). In previous research, student mobility was often included in multiple regression models with various other student covariates that are potential confounding family and student background characteristics (Burkam, Lee, & Dwyer, 2009; Voight, Shinn, & Nation, 2012). Students who become mobile often show pre-existing achievement deficits (Leckie, 2009; Wright, 1999). However, some of the important differences between mobile and non-mobile students, such as motivation, ability, and value placed on education, may not be observed by researchers, which can also confound estimates (Hanushek, Kain, & Rivkin, 2004; Xu et al., 2009). Wright (1999) and Paik and Philips (2002) noted the effect of student mobility was greatly reduced when ethnicity, family, and earlier student achievement were taken into account. As Wright concluded, the general question of how to conceptualize the influence of mobility on student outcomes is problematic (see also Xu et al., 2009).

In addition to disentangling potential confounding effects, previous research on mobility and student outcomes was also hampered by how such processes were modeled using a conventional multilevel modeling framework. In many multilevel studies looking at graduation
outcomes, a strictly hierarchical arrangement is utilized, which assumes individuals remain members of the same school throughout the process being investigated. The reality of investigating processes such as students’ likelihood to graduate from high school on time, however, is that a considerable number of students change high schools one or more times during their educational career.

Until recently, research regarding student mobility has been held back by both a lack of data on student movements and also by the absence of the appropriate multilevel methodology (Leckie, 2009). Two approaches have been commonly used in previous research to address the problem of student movement between schools (Rose, 2017). Both approaches, however, are also known to result in inaccurate estimates of outcomes under investigation (Leckie & Owen, 2013).

In one approach, researchers eliminate mobile students from the analyses. Wright (1999) noted the tendency for districts to acknowledge the disruptive influence of mobility on state assessment results by excluding students who moved during the current year from state assessments. This practice of deleting students who attended multiple schools (i.e., who generated the multiple-membership data structure) from the analysis can often result in a loss of 15 to 20 percent of the data, which can severely bias the results as well as reduce the power to detect effects that may exist in the population (Grady & Beretvas, 2010).

In the second approach, researchers assign mobile students to only one school (e.g., students’ first school or last school). Assigning each individual to only one higher-level unit and then fitting a hierarchical model to multiple-membership data will misattribute response variation to the included levels (Moerbeek, 2004; Tranmer & Steele, 2001), even if a covariate for mobility was added as a student-level predictor. Moreover, incorrectly modelling the
dependency in the data will often lead to obtaining biased standard errors for the predictor variables, particularly those measured at higher levels. This often leads to making misleading inferences about the relative importance of different sources of influence on the outcome (Leckie & Owen, 2013).

Student mobility results in a multiple-membership data structure, a type of cross-classified data structure where the contribution of multiple schools cannot be properly evaluated with a conventional multilevel model (Beretvas, 2011). An important distinction between a conventional hierarchical model, where each student is a member of only one higher-level unit such as a school, and a multiple-membership data structure is that in the latter structure, some individuals are members of more than one higher-level unit from the same classification (Leckie, 2012). Additionally, an important feature of multiple-membership data structures is that the degree to which each individual belongs to each higher-level unit will often vary across those higher-level units. Multiple-membership weights are used to quantify these differences, and this information is used when fitting multiple-membership models (Leckie, 2012). One common means is to weight the model estimates associated with each school attended by the length of time a student spent in those particular school settings. Therefore, estimating multilevel multiple-membership models entails making a number of changes to the specification and estimation of multilevel models that take in the effects of various student and school variables on graduation outcomes while properly incorporating student mobility (Chung & Beretvas, 2012). A limitation of previous multiple-membership studies examining academic outcomes, however, is they primarily focused on demonstrating methods for specifying the multiple-membership models, typically utilizing only one or two covariates, rather than actually addressing the substantive
impact of such models on estimating student and school outcomes using a broad range of student and school covariates (Heck, Reid, & Leckie, 2022). In this study, a cross-classified multiple-membership modeling with the inclusion of a range of student and staff predictors will be examined.

**Theoretical Background**

Although previous research has not conclusively shown a causal connection between student mobility and high school graduation outcomes, the research has advanced a number of theories explaining their relationship. This study draws on ecological systems theories (i.e., Bronfenbrenner, 1994; Bronfenbrenner & Morris, 2006) to understand the relationship between individual factors, family factors, and school factors that influence behaviors of adolescents to graduate from high school on time. This model views students as embedded within a multi-layered ecology which includes more proximal contexts, such as family and school, and more distal factors such as public policies, the economic climate, and societal norms (Center for Promise, 2014, 2015). As the study noted, syntheses of research on student graduation from high school have found that young people who leave school before graduating are affected by the interplay among several factors including individual, family, peer, and school processes.

Center for Promise (2015) researchers found that, controlling for common demographics (e.g., gender, age, race, parent education), students who left school early (or had interrupted enrollments) more frequently reported they were not as prepared for high school, had been homeless, moved homes, were suspended or expelled, experienced a mental health issue, or had friends who dropped out as compared with their peers who graduated on time from high school. Previous research also indicated student mobility has a strong impact on high school graduation,
with a student’s prospect for graduating diminishing if the student changes schools during high school (Gasper et al., 2012; Metzger et al., 2015; Rumberger, 2003). Students who are mobile were more likely to leave school early than students who remain at the same school for all four years of high school (Gasper et al., 2012; Rumberger & Larson, 1998; South et al., 2007). In turn, ninth-grade attendance was a consistent predictor on graduation (Allensworth & Easton, 2007). Allensworth and Easton (2007) noted that students who were highly mobile during elementary and middle school were more likely to have higher absence rates after transitioning to high school. More specifically, students who changed schools three or more times in their last three years of elementary school averaged six more days of absence per semester in high school than students with stable enrollment. Researchers acknowledge that many of the factors that predict student mobility – such as student, family, and school demographics and student performance – also predict school dropout.

The most common causes of student mobility are residential moves related to parents’ employment or other financial instability (Sparks, 2016). Residential mobility, families moving from one home to another, is highly predictive of student mobility (Rumberger, 2003). Residential mobility occurs more with families of low socioeconomic status, whether families are moving to more affordable housing or to better housing (Metzger et al., 2015). Residential mobility is also related to family structure, which may change due to divorce, marriage, or the loss of a head of household (Rumberger, 2003).

Student-related factors also predict student mobility. These factors include poor school performance (low grades or poor assessment results), behavioral problems, absenteeism, and low
motivation (Rumberger, 2003). Students become disengaged from school and, thus, are more likely to transfer to another school.

School-related factors influence student mobility in several ways. Schools with a greater population of retained students and minority students have higher mobility rates whereas schools with better teachers have lower mobility rates (Rumberger, 2003). A school’s policies and practices, such as large class sizes or limited course offerings, may lead students to leave the school due to disengagement (Rumberger, 2003). On the other hand, a school’s rigid policies and practices may lead the school to expel a student or force a student to transfer to another school due to misbehavior or poor performance (Rumberger, 2003).

Early theories regarding student dropout focused on deficit models, suggesting students were primarily to blame for dropping out for reasons that include family challenges such as low socioeconomic status, family structure, high absenteeism, and mobility (e.g., Bryk & Thum, 1989; Valencia, 1997). Researchers often framed dropping out as a personal pathology, deficit, or choice (Mehan, 1997) resulting from a gradual disengagement from schooling (Newmann, Wehlage, & Lamborn, 1992). The process was assumed to begin during elementary school (e.g., falling behind academically or being retained), but students generally did not leave school until during high school as the legal age to leave school in many states was 16 years old (Lee & Burkam, 2003). This perspective placed the blame for failing to graduate directly on students rather than also implicating schools that do not meet the diverse needs of students (Mehan, 1997; Natrriello, 1995).

Research suggests that the school structures (grade configurations, size, grouping practices), institutional processes (assignment of teachers, scheduling processes, classroom
expectations and practices, teacher-student relationships), and policies (discipline, suspension, administrative transfer for disciplinary problems, retention) affect students’ likelihood of dropping out (Croninger & Lee, 2001; Fine, 1991; Heck & Mahoe, 2006; Lee & Burkam, 2003; Riehl, 1999; Rumberger & Thomas, 2000). Previous research noted planned school transition from middle school to high school affects students’ subsequent academic and social integration to high school (Allensworth & Easton, 2007; Alspaugh, 1998). Ninth-grade performance can suffer after transition, and this can have a considerable impact on students’ likelihood to maintain the adequate academic progress needed to graduate (Allensworth & Easton, 2007; Bryk, Sebring, Allensworth, Luppescu, & Easton, 2010; Roderick & Camburn, 1999; Sebring, Allensworth, Bryk, Easton, & Luppescu, 2006). Ninth-grade performance measures such as grade point average (GPA), absences, and the number of course failures were found to be consistent predictors of eventual graduation (Allensworth & Easton, 2007). For example, researchers found in Chicago that more than 40 percent of freshmen finish the year with a GPA lower than 2.0 on a 4.0 scale, with only 25 percent having a GPA of 3.0 or better. Regarding absences, the researchers found over 40 percent of students missed more than two weeks of school per semester. These negative experiences during freshman year put students at risk of not graduating. Allensworth and Easton (2007) concluded that data on early course performance could be used to identify future dropouts and graduates with precision. In fact, once student performance during freshman year was assessed, additional information about students’ backgrounds contributed little to improve prediction of whether students would graduate (Alexander et al., 2001; Allensworth & Easton, 2007).
School procedures that organize course-taking (e.g., tracking, ability grouping, teacher assignment) vary considerably across schools and can result in institutional processes that socially organize dropping out for groups of students (Friedkin & Thomas, 1997; Mehan, 1997, Oakes, 1985). Schools serving predominantly low SES students and racial-ethnic minorities may offer fewer advanced courses and more developmental or remedial courses than schools serving more affluent and racial-ethnic majority students (Rumberger & Thomas, 2000). In addition, school policies and efforts to deal with increased accountability measures may impact student mobility and student withdrawal. Student conduct policies, for example, can influence students’ likelihood of moving or withdrawing (Eitle & Eitle, 2004). The sum of work on how schools affect student early withdrawal suggests that students are more likely to drop out of schools with rigid tracking, unchallenging curricula, poor teaching, and punitive behavioral policies.

The social control function of schools often supersedes the academic function (Watts & Erevelles, 2004), which may serve to advantage some student subgroups while providing barriers to the educational success and social mobility of others (Heck & Mahoe, 2006). Social reproduction theorists suggest that social reproduction processes work differently across school contexts for different constituencies (Gewirtz & Cribb, 2003); that is, in some school settings, subgroups of students may lack the necessary prerequisites or past academic performance record to gain access to more challenging courses needed to prepare for postsecondary education. Social capital networks between students, teachers, counselors, and administrators may reproduce social privilege or marginalization for groups of students; developing such networks may be particularly important for students who may be likely to drop out (Croninger & Lee, 2001). In
other settings, school practices may serve to offset or interrupt social reproduction (Gewirtz & Cribb, 2003).

Figure 1.1, adapted from Rumberger and Thomas (2000), provides a summary of student- and school-level processes from previous research that can impact student graduation outcomes. At the student level, student outcomes are a function of the student’s background and experiences within the school. Student background variables include demographic information, academic background, and student mobility. Student experiences focus on academic and social engagement. These factors impact graduation outcomes, whether a student graduates within four years, takes longer to graduate, or drops out of school. The proposed model thus illustrates the potential of macro-level environments (e.g., Bronfenbrenner & Morris, 2006; Zaccarin & Rivellini, 2002) to influence individual-level behavior in various ways.

**Figure 1.1. Conceptual model examining student persistence versus dropping out.**

The school level represents an aggregated performance of the students within each school. The school outcomes are a function of the school’s context and processes. School context variables include school demographics, or the composition of the student body; student stability, or the percentage of students who are enrolled in the school for the entire school year; and the
school’s structure. School processes involve the academic and social supports provided to students. These factors impact school graduation and dropout rates.

More specifically, in the multiple-membership approach of this study, Figure 1.1 implies that multiple school contexts and processes (i.e., peer and school processes) and individual processes (i.e., individual background, family factors) may moderate mobile students’ academic experiences and their academic and social engagement in ways that can affect their probability of graduating in four years with their cohort. As the figure makes clear, mobility likely does not affect graduation directly; rather, the effect of student mobility on on-time versus other graduation-related outcomes is a proxy for a constellation of other more proximal consequences of mobility (Engberg, Gill, Zamarro, & Zimmer, 2012; Mehana & Reynolds, 2004). More specifically, as Spencer (2017) noted:

…after experiencing student mobility, mobile students can experience a change in school quality, a change in their peer group, a change in the neighborhood surrounding their school and/or home, a change in their access to programs and services, disrupted relationships with school staff and student and parent networks, disrupted instruction in academic courses, and stigma associated with being the new student or the circumstances of the school change. (p. 30)

Thus, student mobility translates to a multitude of factors influencing a student’s likelihood of graduating on-time.

**Research Focus**

Gaining a better understanding of the contributing causes of students failing to graduate on time will help educators to address the needs of students more appropriately to support their
success in graduating. Student mobility may be overlooked as a significant contributing cause to
delayed graduation and dropout rates due to the seemingly low number of students who are
mobile. However, according to the original data set for this study, at least one in five students
enrolled in HIDOE were mobile, transferring from one school to another at least once during the
four years of high school. One goal of this study is to properly incorporate student mobility
between schools utilizing a multiple-membership data structure to determine whether it may
impact on-time graduation. When students move between schools during the period in which we
measure student progress, we should model students as belonging to every school that they
attend and not just their first or final school (Leckie, 2012). As Leckie (2009) argued, when
student mobility is explicitly modelled through multiple-membership models, a downward bias
in the estimates of the school predictors and outcome variances that might otherwise lead us to
underestimate their importance in examining on-time graduation is corrected.

A second goal is to examine how other student and school variables may affect on-time
graduation in two previously used approaches (i.e., deleting mobile students and assigning
mobile students to one school in which they attended) that do not properly account for student
mobility. Do graduation outcomes of students who are mobile differ depending on their
demographics? Overall, the study may help to identify which students are in greater need of
academic supports to persist through high school.

13 The original data set included students who transferred into HIDOE from a non-HIDOE high school, making them
mobile students. For this study, these transfer students were removed from the original data set as data on their
previous schools are missing.
Research Questions

This study will focus on the following questions:

- Does the pattern of student likelihood to graduate on time vary across high schools in the state?
- Does student mobility affect the likelihood of on-time graduation?
- Do student background variables contribute to a student’s likelihood to graduate on time?
- Net of individual covariates, do school contextual variables contribute to a mobile student’s likelihood to graduate on time?

For this study, a multilevel logistic regression was utilized to examine within-school and between-school variables that may also contribute to on-time graduation of students. This approach has several advantages over a single-level analysis. First, this approach yields more accurate estimates of model parameters by considering the clustering of individuals within schools. Students nested in schools may have more similarities with each other than with those in other schools (e.g., see Goldschmidt & Wang, 1999; Heck & Mahoe, 2006; and Norbury, Wong, Wan, Reese, Dillon, & Gerdeman, 2012 for examples of this approach). Second, this approach will better identify potential predictors of students’ likelihood to graduate on time because predictors can be entered into the predictive model at their correct level in the data hierarchy. This facilitates examining possible variations of level-1 effects such as student mobility across units. Third, multilevel approaches (e.g., cross-classified multiple-membership models) permit individuals to be classified at the same level in more than one way (e.g., Leckie, 2012; Zaccarin & Rivellini, 2002).
This study utilized the 2015 graduation cohort of the traditional HIDOE schools. The cohort included students who entered high school as ninth graders in Fall 2011. Data over the course of four school years were analyzed to identify students who graduated on time versus students who remained enrolled beyond four years or left school early during the period of this study.
Chapter 2. Literature Review

This chapter reviews the literature relevant to the goals of the study. First, it highlights an overall theoretical model (e.g., Bronfenbrenner, 1994) that provides a way of understanding the multiple contexts that students may encounter during their educational years. This approach facilitated examining multiple combinations of “contextual clustering” which may jointly influence individual behavior (Engberg et al., 2012; Spencer, 2017; Zaccarin & Rivellini, 2002). As Spencer (2017) emphasized, changing school contextual environments can result in a range of new processes for mobile students (peers, expectations, student-teacher relationships, support services). The view of Bronfenbrenner’s ecological paradigm is that environment, social interaction, and time play essential roles in children’s development. In school settings, the various environmental subsystems (e.g., academic focus and student supports, focus on improving student learning, parent involvement) support teachers and school administrators in developing school environments that are suitable to students’ needs, characteristics, culture, and family background (Taylor & Gebre, 2016). Second, this chapter provides a discussion on recent literature on student mobility, documenting the difficulties of incorporating mobility in studies of student outcomes. More specifically, this discussion forms the underpinnings of the study’s contribution to existing literature regarding student graduation outcomes.

Bronfenbrenner’s Ecological Model

Urie Bronfenbrenner’s general ecological model presents itself as a theoretical paradigm focusing on human development (Bronfenbrenner, 1994). Bronfenbrenner (1994) based his model on two key propositions –
Proposition 1: Human development takes place through proximal processes, “processes of progressively more complex reciprocal interaction between an active, evolving biopsychological human organism and the persons, objects, and symbols in its immediate environment” (p. 38).

Proposition 2: The “form, power, content, and direction of the proximal processes effecting development vary systematically as a joint function of the characteristics of the developing person; of the environment – both immediate and remote – in which the processes are taking place; and the nature of the developmental outcomes under consideration” (p. 38).

The “developing person” in this study is the high school student. This study looks at the proximal processes of high school students in their classrooms within their schools to determine the impact of the students’ background and experiences and of the schools’ context and processes on graduation outcomes.

Bronfenbrenner’s ecological model consists of four environmental levels, with each level impacting the development of each person differently (Onwuegbuzie, Collins, & Frels, 2013). Level 1, the microsystem, involves the immediate environment in which the student interacts. The microsystem is “a pattern of activities, social roles, and interpersonal relations experienced by the developing person in a given face-to-face setting with particular physical, social, and symbolic features that invite, permit, or inhibit engagement in sustained, progressively more complex interaction with, and activity in, the immediate environment” (Bronfenbrenner, 1994, p. 39). The immediate environment in this case is the classroom in which the students interact with their teachers and peers. This is the level at which student-related factors impact a student’s
likelihood to graduate on time, as represented by the horizontal arrows within schools illustrated as the first level of the conceptual model in Figure 1.1.

There are numerous student-related factors that impact graduation outcomes, whether a student graduates on time, needs additional time to graduate, or drops out of school. Dropout rates are often attributed to student demographics, such as socioeconomic status, race and ethnicity, and student academic or social performance (Goldschmidt & Wang, 1999; Rumberger & Palardy, 2005; Rumberger & Thomas, 2000). Student-related factors also predict student mobility. These factors include poor school performance (low grades or poor assessment results), behavioral problems, absenteeism, and low motivation (Rumberger, 2003). Students become disengaged from school and, thus, are more likely to transfer to another school or drop out.

Level 2, the mesosystem, involves the linkages and processes taking place between two or more settings in which the student actively participates (Bronfenbrenner, 1994; Onwuegbuzie, Collins, & Frels, 2013). These settings include the classroom, the school, and the student’s home. It is within the mesosystem that school-related factors impact a student’s likelihood to graduate on time as well as student mobility, as represented by the diagonal arrows in Figure 1.1.

There are several school-related factors that influence graduation outcomes and student mobility. Schools with a greater population of retained students and minority students have higher mobility rates whereas schools with better teachers have lower mobility rates (Rumberger, 2003). A school’s policies and practices, such as large class sizes or limited course offerings, may lead students to leave the school due to disengagement (Center for Promise, 2014, 2015; Hammond, Smink, & Drew, 2007; Partelow, Brown, Shapiro, & Johnson, 2018; Rumberger, 2015). Research suggests that the school structures (grade configurations, size, grouping
practices), institutional processes (assignment of teachers, scheduling processes, classroom expectations and practices), and policies (discipline, suspension, administrative transfer for disciplinary problems, retention) affect students’ likelihood of dropping out (Croninger & Lee, 2001; Fine, 1991; Lee & Burkam, 2003; Heck & Mahoe, 2006; Riehl, 1999; Rumberger & Lim, 2008; Rumberger & Thomas, 2000). The sum of work on how schools affect student early withdrawal suggests that students are more likely to drop out of schools with rigid tracking, unchallenging curricula, poor teaching, and punitive behavioral policies.

Level 3, the exosystem, involves the linkages and processes taking place between two or more settings in which at least one does not involve the student as an active participant but in which events occur that indirectly influences what happens in the setting in which the student actively participates (Bronfenbrenner, 1994; Onwuegbuzie, Collins, & Frels, 2013). There are factors outside of the classroom and school that influence students’ likelihood to graduate on time and student mobility, such as the employment status of their parents and the socioeconomic status of their neighborhood. While such factors do not directly involve the student, the resulting effects may impact the student’s performance in school.

Level 4, the macrosystem, involves the larger cultural context surrounding the student that includes societal belief systems, cultural norms, ideologies, policies, or laws that indirectly influence the person (Onwuegbuzie, Collins, & Frels, 2013). While this study will not delve into the macrosystem, the cultural context in which the student lives does play a role in shaping the student’s values and beliefs, which may in turn influence the student’s likelihood to graduate on time.
Bronfenbrenner’s ecological model provides a framework to define the major constructs of the conceptual model of this study. At the microsystem level, students’ likelihood to graduate on time is influenced by the students’ background. In this study, student background variables include socioeconomic status, gender, ethnicity or race, and identified academic needs, such as services received through special education or the English learner program. The students’ background may influence the students’ experience within the classroom, impacting student engagement academically, for which variables include assessment scores, as well as socially, including variables such as attendance. These experiences affect student outcomes, whether the student graduates on time, needs additional time to graduate, or drops out of school.

At the mesosystem level, students’ likelihood to graduate on time is influenced by the school context and school processes. This study will focus on school context variables, which include student composition (student enrollment, SES, race and ethnicity, and identified academic needs), student mobility, and the structure of the school. These school context variables influence the student’s experience within the school. The academic and social supports the school provides through its school processes may moderate student experiences, impacting student outcomes. These school processes variables include teacher stability and experience; the school’s overall performance as determined through the statewide school accountability system; and the school’s parent perception survey results.

By viewing students at the microsystem level and their relationship with their schools at the mesosystem level, we can better understand how the school context and processes moderate the individual student’s likelihood to graduate, whether the student is mobile or not. Factors at the exosystem level, which include the greater school community, may also moderate student
experiences in school and influence graduation outcomes. Teacher and parent perceptions as determined through school climate surveys may serve as a school community variable.

Through this study, the factors influencing student graduation outcomes are examined to determine the supports needed to improve a mobile student’s likelihood to graduate on time. Understanding how students’ background and the context of the schools these students are enrolled in may impact student engagement will help to better identify the school processes that will increase their probability of graduating on time.

**Incorporating Student Mobility**

Student mobility has been investigated in a variety of previous school achievement and graduation studies (e.g., Alspaugh, 1998; Fiel, Haskins, & Turley, 2013; Gillespie, 2013; Goldschmidt & Wang, 1999; Grigg, 2012; Heck & Mahoe, 2006; Wright, 1999; Xu et al., 2009). Xu et al. (2009) found that minority, low-income, and limited-English-proficient students as well as students whose parents have lower education attainment were at higher risk of making non-promotional school changes than their peers. They were also more likely to move frequently, which has been found in previous research to harm student academic progress. Within more homogeneous subgroups of students, Xu et al. (2009) found that school mobility had negative effects for math, but no effect for reading among minority, limited-English-proficient, and low-income students and students who moved within districts (regardless of their racial/ethnic background or poverty status). Other recent studies found mixed impacts of student mobility on academic performance (e.g., de la Torre & Gwynne, 2009; Dupere, Archambault, Leventhal, Dion, & Anderson, 2015; Grigg, 2012).
Leckie (2009) found a negative relationship between student mobility and academic achievement, the strength of which depended greatly on the nature and timing of these moves. More specifically, negative effects were larger for within-year compared to between-year moves, for moves at older ages, and for students who changed schools with no accompanying home move. The sum of this research suggests student mobility is common among students during their elementary and secondary years and can adversely affect academic learning due to the disruption of school-based social ties and academic routines.

Studies also examined student mobility more generally as a predictor of graduation outcomes (e.g., Alspaugh, 1998; Grim, 2019; Heck & Mahoe, 2006; La Torre, Leon, Wang, & Cai, 2019; Norbury et al., 2012). Over two decades ago, Alspaugh (1998) noted that as the number of school-to-school moves increased within a school district, so did schools’ dropout rates, indicating student mobility impact graduation outcomes in addition to individual variables (e.g., family SES) identified in previous research conducted during the 1980s and 1990s. School size also appeared to contribute to schools’ dropout rates and later high school transition (grade 10) was associated with higher school dropout rates. Heck and Mahoe (2009) noted that changing schools before high school did not affect transition to high school (defined in terms as still enrolled in the Spring of grade 10); however, mobility after transition to high school negatively affected persistence for both one move and two or more moves. More specifically, students who moved once had decreased odds of graduating of approximately 66 percent compared to their peers who did not move and students who moved two or more times had reduced odds of approximately 69 percent compared to their stable peers, holding other student-level and school variables in the persistence model constant. Norbury et al. (2012) found ninth-
grade indicators (e.g., course credits earned and failures) were consistent predictors of graduation, after controlling for student background characteristics and grade 8 assessment test scores. More recently, Grim (2019) investigated the impact of student mobility (i.e., number and type of school moves) on student achievement and graduation status, controlling for background and contextual variables including gender, ethnicity, school tier, and SES. Grim found that mobility had a consistently negative impact on a student’s likelihood to graduate with the effect of one move being less than the effect of multiple moves.

As noted in Chapter 1, in most extant studies, mobility was not properly incorporated into the model to adjust the student-level and school-level model estimates for mobile students. In one recent large scale study that did incorporate a multilevel multiple-membership data structure to incorporate student movement between schools, La Torre et al. (2019) found that participation in the Los Angeles Unified School District’s Afterschool Enrichment Program (LA’s BEST) during elementary school years, serving primarily Hispanic, low SES, and English language learners, produced stronger high school graduation rates among more frequent attendees than a matched sample of students who did not attend the program. More frequent attendees were five percent less likely to dropout and six percent more likely to complete high school on time than were the matched control students in the same elementary schools who never participated in the program (La Torre et al., 2019).

The theoretical and empirical literature that frames this study provides a way for researchers to study how student mobility influences students’ likelihood to graduate on time within Hawai‘i’s public schools. A limitation of previous research on student mobility and student high school graduation is that the set of studies did not incorporate student mobility
directly into the analyses through weighting the duration of the time mobile students spent in other school settings, which directly impacts the estimation of the influence of multiple school environments on mobile students’ graduation outcomes. Given this previous limitation, there is a need for research that utilizes multilevel modeling of multiple-membership data structures to allow for student mobility to be directly incorporated into multilevel investigations of individual and school environmental effects on educational attainment (Leckie, 2009). This will provide a more accurate estimation of the impact of student mobility, informing the supports and resources needed to facilitate student success for mobile students.
Chapter 3. Method

Data Source

The study is based on the HIDOE 2015 graduation cohort. The existing data set included 12,359 students who begin as first-year ninth-grade students enrolled in a HIDOE school in School Year 2011-12. All public schools with high school students (N = 41) were included in the data with the exception of the public charter schools and the two schools with special populations. Of the 12,359 students included in the data set, 9,080 (73.5%) students graduated on time; 351 students continued beyond four years of high school (2.8%); 1,557 students dropped out (12.6%); and 1,371 (11.1%) were transfer students who left HIDOE for a variety of reasons (e.g., left the state, attended a private school, homeschooled). For this study, the transfer students and 28 students who could not be placed in a school for ninth grade were removed from the data set. Thus, only students who entered the 41 public schools at the beginning of School Year 2011-12 as ninth graders were included in the data set used in this study. The final data set included 10,960 students, with 9,079 students who graduated on time; 348 students who continued beyond four years of high school; and 1,532 students who dropped out during the four years.

Variables in the Analyses

Graduation outcome. The outcome for this study was on-time graduation, defined as graduating within four years of high school (coded 1). Students continuing enrollment beyond four years and students who dropped out were coded as 0.

Student variables. Student predictors included background variables, academic variables, and mobility. Student background variables included gender (coded female =1); socioeconomic status of the family, as determined by student eligibility for free or reduced-cost
meals (coded 1 versus 0 = else); ethnicity, with federal designations dummy coded (i.e., African American = 1, else = 0; Hispanic = 1, else = 0; Asian/Pacific Islander = 1, else = 0; Native American = 1, else = 0; and White serving as the reference group); and supports received such as special education (coded 1, else = 0) and the English learner program (coded 1, else = 0). Student academic variables include tenth-grade math proficiency, as measured by the annual statewide assessment (coded 3 = exceeded, 2 = met, 1 = approaching, 0 = not met), and ninth-grade attendance (coded as days attended).

Student mobility was determined through exit and enrollment data (i.e., students that exited one school and enrolled in another during the four-year period). Table 3.1 provides the data on student mobility. Of the 10,960 students within this cohort, 9,817 students (89.6%) remained in the same school throughout the four-year period; 1,046 students (9.5%) changed schools once; 89 students (0.8%) changed schools twice; and 8 students (0.1%) changed schools three times. A total of 1,143 students within the 2015 cohort, or 10.4 percent, were mobile. The cohort data regarding high school mobility were broadly consistent with the 1998 National Assessment of Educational Progress (NEAP), in which approximately 10 percent of twelfth graders had changed schools at least once in the previous two years.

<table>
<thead>
<tr>
<th>Moves</th>
<th>Frequency</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9817</td>
<td>89.6</td>
</tr>
<tr>
<td>1</td>
<td>1046</td>
<td>9.5</td>
</tr>
<tr>
<td>2</td>
<td>89</td>
<td>0.8</td>
</tr>
<tr>
<td>3</td>
<td>8</td>
<td>0.1</td>
</tr>
<tr>
<td>Total</td>
<td>10960</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Table 3.2 provides a crosstabulation of students’ graduation status by mobility. As the table suggests, students who remained in the same school were more likely to graduate on time.
than students who transferred from one school to another school at least once during high school. This is evident by the decrease in the percentage of students who graduated on time for each number of moves (with the exception of three moves).

<table>
<thead>
<tr>
<th>Table 3.2. Student Graduation Status by Mobility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graduated on Time</td>
</tr>
<tr>
<td>Mobility</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>% within graduated on time</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>% within graduated on time</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>% within graduated on time</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>% within graduated on time</td>
</tr>
<tr>
<td>Total</td>
</tr>
<tr>
<td>% within graduated on time</td>
</tr>
</tbody>
</table>

Pearson chi-square (3 df) = 119.424, p < .001

<table>
<thead>
<tr>
<th>Table 3.3. Descriptive Statistics for Student Predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
</tr>
<tr>
<td>---</td>
</tr>
<tr>
<td>Mobility</td>
</tr>
<tr>
<td>Gender (female)</td>
</tr>
<tr>
<td>Socioeconomic status</td>
</tr>
<tr>
<td>Special education</td>
</tr>
<tr>
<td>English learner program</td>
</tr>
<tr>
<td>Math proficiency</td>
</tr>
<tr>
<td>Ninth-grade attendance</td>
</tr>
<tr>
<td>Ninth-grade GPA</td>
</tr>
<tr>
<td>Ethnicity (White)</td>
</tr>
<tr>
<td>Ethnicity (Asian/Pacific Islander)</td>
</tr>
<tr>
<td>Ethnicity (Hispanic)</td>
</tr>
<tr>
<td>Ethnicity (African American)</td>
</tr>
<tr>
<td>Ethnicity (Native American)</td>
</tr>
<tr>
<td>On-time graduation</td>
</tr>
</tbody>
</table>
Table 3.3 presents the descriptive statistics for the student predictors. The data suggest low proportions of African American, Hispanic, and Native American students, as well as students enrolled in English learner programs.

Table 3.4. Student-Level Variables for Movers and Non-Movers with Univariate Tests of Equality of Group Means

<table>
<thead>
<tr>
<th>Variable</th>
<th>Did not move</th>
<th>Moved one or more times</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (female)</td>
<td>0.476</td>
<td>0.466</td>
<td>0.46</td>
<td>0.708</td>
</tr>
<tr>
<td>Socioeconomic status</td>
<td>0.435</td>
<td>0.63</td>
<td>56.03</td>
<td>0.000</td>
</tr>
<tr>
<td>Special education</td>
<td>0.105</td>
<td>0.151</td>
<td>10.62</td>
<td>0.000</td>
</tr>
<tr>
<td>English learner program</td>
<td>0.039</td>
<td>0.048</td>
<td>1.58</td>
<td>0.191</td>
</tr>
<tr>
<td>Math proficiency</td>
<td>2.383</td>
<td>1.954</td>
<td>63.67</td>
<td>0.000</td>
</tr>
<tr>
<td>Ninth-grade attendance</td>
<td>170.567</td>
<td>162.888</td>
<td>73.61</td>
<td>0.000</td>
</tr>
<tr>
<td>Ninth-grade GPA</td>
<td>0.348</td>
<td>0.348</td>
<td>68.43</td>
<td>0.000</td>
</tr>
<tr>
<td>Ethnicity (white)</td>
<td>0.109</td>
<td>0.082</td>
<td>4.51</td>
<td>0.004</td>
</tr>
<tr>
<td>Ethnicity (Asian/Pacific Islander)</td>
<td>0.822</td>
<td>0.805</td>
<td>1.30</td>
<td>0.274</td>
</tr>
<tr>
<td>Ethnicity (Hispanic)</td>
<td>0.048</td>
<td>0.094</td>
<td>14.3</td>
<td>0.000</td>
</tr>
<tr>
<td>Ethnicity (African American)</td>
<td>0.016</td>
<td>0.018</td>
<td>0.16</td>
<td>0.921</td>
</tr>
<tr>
<td>Ethnicity (Native American)</td>
<td>0.005</td>
<td>0.042</td>
<td>0.76</td>
<td>0.514</td>
</tr>
<tr>
<td>On-time graduation</td>
<td>0.841</td>
<td>0.717</td>
<td>40.23</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 3.4 provides an indication of differences with respect to background and academic variables between students who did not move schools during their four years of high school and students who moved at least once during their high school years. Table 3.4 also presents a univariate $F$ test of whether non-movers and movers differed according to each of the student variables in the study (without controlling for the effects of the other indicators). Among the ethnicity indicators, proportions of Hispanic and White students were significantly different across movers and non-movers. Family socioeconomic status, ninth-grade attendance and GPA,
math proficiency, and special education status also differed across mobility status. Finally, on-time graduation differed across mobility. In considering the constellation of individual-level variables that differentiate mobile versus non-mobile students in Table 3.4, Leckie (2009) notes the parameter estimates of these indicators should not be interpreted causally, since they are additionally likely to reflect systematic differences in the unobservable characteristics of mobile and stable students which themselves may be important determinants of students’ likelihood to graduate on time. More specifically, mobile students may have unobserved characteristics that lead to poorer progress toward graduation irrespective of moving and, if this is the case, the reported associations will overstate any genuine negative causal effect of mobility.

Table 3.5. Descriptive Statistics for School Predictors

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student enrollment</td>
<td>41</td>
<td>266</td>
<td>2768</td>
<td>1263.61</td>
<td>626.49</td>
</tr>
<tr>
<td>Student stability</td>
<td>41</td>
<td>0.848</td>
<td>0.969</td>
<td>0.92</td>
<td>0.03</td>
</tr>
<tr>
<td>Student meal status</td>
<td>41</td>
<td>0.136</td>
<td>0.837</td>
<td>0.48</td>
<td>0.18</td>
</tr>
<tr>
<td>Teacher stability</td>
<td>41</td>
<td>0.450</td>
<td>0.770</td>
<td>0.65</td>
<td>0.08</td>
</tr>
<tr>
<td>Teacher experience</td>
<td>41</td>
<td>8.800</td>
<td>16.600</td>
<td>12.29</td>
<td>2.08</td>
</tr>
<tr>
<td>Math proficiency</td>
<td>41</td>
<td>0.080</td>
<td>0.660</td>
<td>0.42</td>
<td>0.14</td>
</tr>
<tr>
<td>Parent perception of support</td>
<td>41</td>
<td>0.590</td>
<td>0.853</td>
<td>0.77</td>
<td>0.06</td>
</tr>
<tr>
<td>Parent perception of school</td>
<td>41</td>
<td>0.438</td>
<td>0.826</td>
<td>0.72</td>
<td>0.07</td>
</tr>
</tbody>
</table>

School variables. School predictors, summarized in Table 3.5 for first schools, included student composition variables, teacher composition variables, and school performance variables. Student composition variables were student enrollment, the number of students enrolled; student stability, defined as the proportion of students who remained at the school all year; and student federal meal status, defined as the proportion of students who were eligible for free or reduced-cost school meals. Note that at the beginning of the study, the average proportion of students
who remained at the same high school for the year was approximately 0.92 (or 92%, with standard deviation of approximately 3%). This suggests considerable stability of high school students across the state (i.e., with a low of 0.85 and high of 0.97 across high schools). Teacher composition variables included teacher stability, defined as the proportion of teachers who remain at the school for at least five years, and teacher experience, or the average number of years the teachers taught. School performance variables included math proficiency, as measured by the annual statewide assessment (defined as the proportion of students who met or exceeded the achievement standard), and parent perceptions on student supports and school improvement (both defined as the proportion of parents who agreed or strongly agreed with the items comprising each construct), as measured by the Hawai‘i School Quality Survey. Both constructs were found to have acceptable internal consistency coefficients (i.e., above 0.80) in previous research (e.g., Heck & Hallinger, 2014).

Analyses

Defining the Basic Two-Level Logistic Regression Model

This study utilizes a series of multilevel binary logistic regression model with within-school and between-school components to predict students’ likelihood to graduate on time (within four years) versus continuing to be enrolled or dropping out. All models were estimated using SPSS Version 28. For a two-level formulation with binary outcome, which is summarized as the ratio of the event occurring versus not occurring \( \frac{\pi_{ij}}{1-\pi_{ij}} \), the level-1 model can be defined as the following:

\[
\eta_{ij} = \ln \left( \frac{\pi_{ij}}{1-\pi_{ij}} \right) = \beta_0 + \beta_{1j}x_{1ij} + \beta_{2j}x_{2ij} + \cdots + \beta_{qj}x_{qij}, \quad (3.1)
\]
where $\eta_{ij}$ is the predicted log odds for individual $i$ in group $j$, $\beta_{0j}$ is an intercept, $x_{1ij}$ to $x_{qij}$ are student-level predictors (e.g., mobility, gender, socioeconomic status, math proficiency), and $\beta_{1j}$ to $\beta_{qj}$ are corresponding log odds coefficients. Note that there is no residual variation ($\epsilon_{ij}$) at the individual level of the model since the outcome is dichotomous.

At level 2 of this model, a set of school-level predictors (e.g., quality of student support, enrollment size, teacher stability, proportion of student proficient in math) can be added to explain variability in the log odds of graduating on time across schools in the data set:

$$
\beta_{0j} = \gamma_{00} + \gamma_{01}z_{1j} + \gamma_{02}z_{2j} + \cdots + \gamma_{0q}z_{qj} + u_{0j}.
$$

The variation in intercepts is described by a school-level intercept ($\gamma_{00}$), school-level predictors ($z_{1j}$ to $z_{qj}$), and a random effect ($u_{0j}$). Note that student predictors were treated as fixed within schools ($u_{1j}$ to $u_{qj} = 0$).

Typical steps in multilevel modeling involve (1) partitioning the variance into its within-school and between-school components, (2) developing a within-school model with mobility added, (3) adding the full set of student predictors, and (4) developing school-level models to explain differences in school graduation rates.

The basic unconditional model (i.e., with no predictors) includes only an intercept and a school random effect, as the level-1 variance is scaled to a logistic distribution (i.e., $\pi^2/3$) or approximately 3.29 when the outcome is dichotomous:

$$
\eta_{ij} = \ln \left( \frac{\pi_{ij}}{1-\pi_{ij}} \right) = \beta_{0j} = \gamma_{00} + u_{0j}.
$$

37
The basic unconditional model can be used to decompose the variance in log odds of graduating on time into separate school and student components:

\[ p = \frac{\sigma_{Between}^2}{\sigma_{Between}^2 + 3.29}. \]  

(3.4)

**Approaches Examined in the Study**

Three approaches were considered for this study with respect to examining students’ probability of graduating on time versus continuing to be enrolled or dropping out.

**Mobile-students-removed approach.** The first approach entails the deletion of all mobile students from the data set (e.g., McRoach, O’Connell, Reis, & Levitt, 2006). With the removal of mobile students, the number of students included in the data set was 9,817 students nested within the state’s 41 public schools serving students in grades nine through twelve. In this approach, the final model included school and student-level predictors, as specified in Equations 3.1 and 3.2, except for student mobility.

**First-school approach.** The second approach includes the mobile students but only accounts for the first high school in which they are enrolled, not the subsequent schools in which the subset of mobile students transferred to during their high school years. School-level predictors of the first school in which the students were enrolled are assumed to account for school-level differences in the graduation outcome. This represents the analytic approach used in the majority of past studies (Goldstein, Burgess, & McConnell, 2007). For example, Norbury et al. (2012) examined on-time graduation using freshman at-risk indicators but did not account for student mobility in their multilevel logistic regression models.
The number of students for this approach was 10,960 nested in the 41 high schools. The level-1 and level-2 models are as specified in Equations 3.1 and 3.2, with mobility as a student-level predictor. Similar to Norbury et al. (2021), who found no variability in student academic or demographic indicators on graduation outcomes across schools, these models assume that schools have constant effects on individuals’ graduation outcomes, irrespective of the effects of specific student-level characteristics. Note that a possible random mobility slope between schools was tested but found to fit the data significantly worse than the model with fixed mobility slope ($\Delta X^2 = 19.98$, 1 df, $p < 0.001$). This result suggested the overall mobility-achievement slope was a constant size between schools, so the slope was fixed to 0 for subsequent analyses.

**Multiple-membership approach.** The third approach models the multiple-membership data structure for mobile students, where some individuals may be nested within multiple higher-level units from the same classification, by including weights describing the proportion of time spent in each school attended (Leckie, 2012). This approach represents the contribution of this study to examining the probability of students’ on-time graduation while also accounting for student mobility correctly in estimating the effects of student-level and school-level variables on the outcome. It is important to recognize the contribution or effect that every school has on student educational outcomes to avoid misattributing response variation to the included levels, which could result in misleading conclusions about the relative importance of different variables on the outcome (Leckie, 2012). Examining this type of cross-classified multiple-membership dataset does not require that factors associated with random effects be hierarchical factors in the design. The same basic model specification can be used for data with nested or partially crossed
factors; that is, the strict nesting for students who did not move or partial crossing (or multiple-membership structure) for mobile students is determined from the structure of the data rather than the specification of the model (Bates, 2011). The data for these models included 10,960 students in 41 high schools of which a small percentage of students (approximately 1.5%) transferred to and graduated from a HIDOE charter school.14

Because multiple-membership data structures are not strictly hierarchical, a modification to the standard hierarchical notation must be made (Leckie, 2012). Browne, Goldstein, and Rasbash (2001) developed a classification notation system to provide a simplified means of specifying the potential multiple higher units of which some individuals may be members. In classification notation, individuals are labeled as classification 1. Convention has it that student-level (1) superscripts and subscripts do not appear in the model equation but are implicit. In this notation, $i (i = 1, \ldots, N)$ indexes individuals. The separate classifications of higher random effects are then labeled using superscripts and subscripts (2), (3), and so forth, to identify the different sets of random effects and their associated variance (and any covariance) parameters. In this study, individual students were members of one to four schools.

An unconditional multiple-membership model is also useful in determining how much of the variance in student likelihood of graduating on time varies across schools. The model can be modified from Equation 3.1 as follows:

$$\eta_i = \ln \left( \frac{\pi_i}{1-\pi_i} \right) = \beta_0 + \sum_{h=\text{school}(i)} w_{hi}^{(2)} u_h^{(2)}$$

$$u_h^{(2)} \sim N(0, \sigma_u^{(2)})$$

14 Charter schools were not included because the school-level data were not complete and few students graduated from any particular charter school.
where $\eta_i$ is the expected log odds for individual $i$ ($i = 1, \ldots, 10,960$), $\beta_0$ is the overall mean log odds for on-time graduation for schools, and $\sum_{h \in \text{school}(i)} W_{h,i}^{(2)} u_h^{(2)}$ is a weighted sum of school effects where the multiple-membership weight $W_{h,i}^{(2)}$ measures the proportion of time student $i$ attended school $h$ ($h = 1, \ldots, 41$) with associated effect $u_h^{(2)}$. The school-level variances ($u_h^{(2)}$) are assumed to be independent and normally distributed with zero means and constant variances. In terms of interpreting the unconditional multiple-membership model in Equation 3.5, the total variance in log odds for graduating on time is decomposed into its between- and within-group components, which may be defined as the variation in students’ log odds of on-time graduation attributable to schools (versus the total variation) and depends on how students are mobile across the 41 high schools (Leckie & Owen, 2013). As Equation 3.5 suggests, for the subset of students who subsequently moved between schools, the residual variance attributed to schools is determined by incorporating the length of time students attended each school.

In multiple-membership models, the weights are typically defined to sum to 1.0 for each student. For example, if a student attended one school for ninth grade and then attended a second school from tenth through twelfth grades, the weights would be defined as 0.25 and 0.75 (which add to 1.0 for the four years of the study). A student who did not move would receive a weight of 1.0, indicating attendance in only one school. Following Leckie and Bell (2013), in this type of weighted formulation, schools are indexed by $h$ rather than by $j$ to avoid any potential confusion when the cross-classified multiple-membership model is reformulated into a two-level hierarchical model (as in Equations 3.1 and 3.2) after constructing the multiple-membership weights. Table 3.6 provides an example of four students (ID 1, 2, 3, and 4) and the schools in which they were enrolled. Student 1 only attended School 1 (weighted as 1.00); thus, for teacher
experience for Schools 1 through 41, only the teacher experience of 0.60 (60%) for School 1 would contribute to Student 1’s probability of graduating on time. Student 2 attended School 1 for two years, or half the time (0.50), and School 2 for two years (0.50). Thus, the teacher experience predictor would be weighted 0.50 for School 1 and 0.50 for School 2 with teacher experience of 0.45 attributing to Student 2’s likelihood to graduate on time:

\[(0.50)(0.60) + (0.50)(0.30) = 0.45.\]

For Student 3, a teacher experience of 0.275 contributes to her likelihood to graduate on time:

\[(0.25)(0.60) + (0.25)(0.30) + (0.50)(0.10) = 0.275.\]

For Student 4, the teacher experience predictor attributes 0.30 to Student 4’s likelihood of graduating on time:

\[(1.0)(0.30) = 0.30.\]

### Table 3.6. Example of Multiple-Membership Weights

<table>
<thead>
<tr>
<th>Student ID</th>
<th>Proportion of 4 years of High School Enrolled</th>
<th>Teacher Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>School 1</td>
<td>School 2</td>
</tr>
<tr>
<td>1</td>
<td>1.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>3</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>4</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

A general level-1 model for multiple-membership data can be written as follows:

\[\eta_i = \ln \left( \frac{\pi_i}{1 - \pi_i} \right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_q x_{qi} \sum_{\text{school}(i)} w_{h,i}^{(2)} u_h^{(2)}\]

\[u_h^{(2)} \sim \mathcal{N}(0, \sigma_u^{(2)}) ,\]  

where \(\eta_i\) is the expected log odds for individual \(i\) \((i = 1, \ldots, 10,960)\), \(\beta_0\) is an adjusted school intercept, \(x_{1i}\) to \(x_{qi}\) are level-1 predictors, \(\beta_1\) to \(\beta_q\) are regression coefficients, and

\[\sum_{\text{school}(i)} w_{h,i}^{(2)} u_h^{(2)}\]

is a weighted sum of school effects where the multiple-membership weight \(w_{h,i}^{(2)}\) measures the proportion of time student \(i\) was in school \(h\) \((h = 1, \ldots, 41)\) with associated
Additionally, it is assumed that the school effects ($u_h^{(2)}$) are independent and normally distributed with zero means and constant variances. In these models, the assumption again is that schools have constant effects on individuals’ graduation outcomes, irrespective of the effects of specific individual-level characteristics (e.g., mobility, gender, ethnicity) on outcomes.

Between schools, a set of predictors can be added to determine which school-level contextual variables might affect students’ log odds of graduating on time. For mobile students, the predictors represent estimates of the effects of multiple school environments on the log odds of graduating on time. The combined two-level model, again expressed using classification notation, is written as follows using weighted mean teacher experience as an example school predictor (denoted as $z_{1j}$ to $z_{qj}$ in Equation 3.2):

$$\eta_i = \ln \left( \frac{\pi_i}{1-\pi_i} \right) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_q x_{qi} + \beta_{q+1} \overline{tchexp}_i \sum_{h \in \text{school}(i)} w_{h,i}^{(2)} u_h^{(2)}$$

$$u_h^{(2)} \sim N(0, \sigma_u^{2(2)})$$

where $\overline{tchexp}_i = \sum_{h \in \text{school}(i)} w_{h,i}^{(2)} tchexp_h$ indicates a weighted average of years of teacher experience estimated across the subset of high schools each mobile student attended proportional to the duration of time the student attended that school as illustrated in the example in Table 3.6 (Leckie & Owen, 2013). Before the complete multiple-membership model with school variables can be estimated, the weighted average of school scores for each predictor must be generated for each student with regards to the particular high schools each mobile student attended and saved.

---

15 A possible random mobility-graduation slope was investigated, but the model produced a warning that the model did not converge on a solution (Final Hessian matrix is not positive definite. Validity of the model is uncertain.). Therefore, the mobility-graduation slope was fixed in subsequent models.
into the dataset. The final multiple-membership model was therefore similar to Equations 3.1 (level 1) and 3.2 (level 2) with weighted averages for the final set of school-level predictors in each of the school settings mobile students attended (e.g., School 1, School 4, and School 7) rather than just the school predictors associated with the first school attended.

**Analysis of main effects and interactions.** The primary comparisons between approaches in Models 2 through 4 were conducted using main effects only. Previous quantitative analyses on persistence, however, have often treated student background (e.g., ethnicity, family SES) as controls. By focusing on “average” effects, researchers may miss opportunities to provide more fine-grained analyses of how student-level variables intersect with student mobility in explaining on-time graduation. In addition, weighted school context indicators may moderate the effect of student mobility on graduation outcomes (Heck & Mahoe, 2006). As an additional step, possible multiple-membership models were then conducted by examining interactions between student-level variables and mobility and between school-level variables and mobility (i.e., cross-level interactions). An interaction can be interpreted as the amount of change in the logit of \( y \) with respect to \( x \) when \( z \) (for example, family SES) changes by one unit. More specifically, does the dependence of a student’s on-time graduation on whether or not the student is mobile also depend on family SES? Non-significant interactions were removed from the final model presented.
Chapter 4. Results

The results of the study are organized by the study’s research questions and the three modeling approaches investigated.

Research Question 1: Does Student Odds of Graduating on Time Vary Across Schools?

Table 4.1. Unconditional Model for the Three Approaches

<table>
<thead>
<tr>
<th>Mobile-Students-Removed Approach</th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Odds (Std. Error)</td>
<td>Odds Ratio</td>
<td>Sig.</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.707 (0.079)</td>
<td>5.510</td>
</tr>
<tr>
<td>Random Effects Variance</td>
<td>0.205* (0.055)</td>
<td>0.177* (0.048)</td>
</tr>
<tr>
<td>ICC</td>
<td>0.057</td>
<td>0.051</td>
</tr>
<tr>
<td>Deviance</td>
<td>8421.54</td>
<td>9868.74</td>
</tr>
</tbody>
</table>

Note: SPSS provides a Wald Z test of the statistical significance of the level-2 variance components regarding whether the estimate is significantly different from 0 (*p < .001). The test should be considered as approximate only, however, since variance components are not normally distributed; that is, variances must be positive, so they are typically skewed (Hox, 2010). It also tends to underperform with small samples of level-2 units. In this study, further examinations of model fit to the data were conducted using likelihood ratio tests, which can be developed from the model's deviance statistic (Hox, 2010; Leckie & Owen, 2013).

Table 4.1 provides the unconditional models examining the average log odds (and odds ratio) of graduating on time across high schools and the variability in graduating on time. The data indicates that the average log odds of graduating on time are similar for the first approach in which mobile students were removed and the second approach in which only the first school of enrollment was considered. The log odds estimates were 1.707 and 1.603, respectively, with $\rho < 0.001$. The corresponding odds ratios were 5.510 and 4.966, respectively. This suggests that students were approximately 5.5 and 5.0 times more likely to graduate on time than to continue
to be enrolled or leave school early. Neither of these approaches, however, incorporated student mobility into the model correctly for mobile students.

For the cross-classified multiple-membership approach, the estimated log odds of on-time graduation was 1.604 and corresponding odds ratio coefficient was approximately 5.0. Without the student-level and school-level predictors, the data of the first-school approach and the multiple-membership approach were similar.

Table 4.2. Predicted Probability of On-Time Graduation

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>On-time graduation</td>
<td>41</td>
<td>0.656</td>
<td>0.923</td>
<td>0.824</td>
<td>0.062</td>
</tr>
</tbody>
</table>

For the random effects, the mobile-students-removed approach estimated the school-level variability in average log odds of graduating across the set of high schools as 0.205 with a coefficient of 0.177 for the first-school approach and 0.203 for the multiple-membership approach. For the multiple-membership model, in particular, predicted proportions of students graduating on time ranged from 0.66 to 0.92 with an on-time graduation mean of 0.824 (see Table 4.2). This weighted estimate of on-time graduation was slightly lower than the unweighted estimate of 0.83 of on-time graduation in Table 3.3. Note that for the random effects in Table 4.1, the variance components were initially tested for statistical significance using Wald Z tests and the variances were found to be significantly different from 0. This test should be interpreted cautiously, however, because variance components are not normally distributed, one reason being that variances cannot be smaller than 0 (Hox, 2010). The intraclass correlation coefficients (ICC) indicated that the mobile-students-removed approach estimated the between-school variability across schools as 0.057, which was slightly higher than the first-school approach (0.051) and about the same as the multiple-membership approach (0.058). For the multiple-
membership approach, the ICC of 0.058 (or nearly 6%) described the expected degree of similarity (or homogeneity) between responses within a given school for two students who attended only one school (Leckie & Owen, 2013). For students who attended more than one school, the similarity in responses can be estimated depending on the number of schools attended and the duration (e.g., see Leckie & Owen, 2013). The ICC for all three models indicated that the pattern of student likelihood to graduate on time varied across high schools.

The deviance is an indicator of how well the model fits the data. The lower the deviance, the less the discrepancy and better the fit. The deviance for the cross-classified multiple-membership approach (9,848.48) was 20.3 smaller than the deviance for the first-school approach (9,868.74), indicating a better model fit, with differences of 5.0 or more considered substantial (Lunn et al., 2013). The deviance for the mobile-students-removed approach was not comparable to the other two approaches due to the deletion of students creating a different dataset of students.

Research Question 2: Does Student Mobility Affect the Odds of Graduating on Time?

Student mobility was added to the models to determine whether mobility affects the log odds of graduating on time. These models are presented in Table 4.3. The mobile-students-removed approach is not presented since mobile students were eliminated in that model.

In the first-school approach, mobility was statistically significant and negatively affected on-time graduation, as indicated by the negative log odds (Log Odds = -0.605, p < 0.001). The corresponding odds ratio of 0.546 suggested that students who moved once experienced a 45 percent (1 - 0.55 = 0.45) decrease in the odds of graduating on time compared to their peers who
did not move. For two moves, the odds of graduating on time would be decreased by approximately 70 percent (0.546*0.546 = 0.298 and 1-0.298 = 0.702).

Table 4.3. Student Mobility Model for the Three Approaches

<table>
<thead>
<tr>
<th></th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Odds (Std. Error)</td>
<td>Odds Ratio</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.690 (0.072)</td>
<td>5.419</td>
</tr>
<tr>
<td>Mobility</td>
<td>-0.605 (0.063)</td>
<td>0.546</td>
</tr>
</tbody>
</table>

Random Effects

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance</td>
<td>0.165 (0.045)</td>
</tr>
<tr>
<td>Deviance</td>
<td>9780.38</td>
</tr>
</tbody>
</table>

Similarly, the multiple-membership approach, which incorporated student mobility into the model estimates, indicated that mobility was also negatively, and significantly, related to on-time graduation (-0.624) with corresponding odds ratio somewhat smaller (OR = 0.536). More specifically, predicted estimates of student mobility across the 41 schools ranged from 0.085 to 0.164, with a mean of 0.108 and standard deviation of 0.018 (see Table 4.4). Weighted for mobility, students who moved once experienced an average 46 percent decrease in the odds of graduating on time; for two moves, a 71 percent decrease in the odds of graduating on time would be experienced compared to their peers who did not move during high school.

Table 4.4. Predicted Probability of Student Mobility

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobility</td>
<td>41</td>
<td>0.085</td>
<td>0.164</td>
<td>0.108</td>
<td>0.018</td>
</tr>
</tbody>
</table>

The deviance statistic indicated that the cross-classified multiple-membership approach was a better model fit than the first-school approach (9,753.84 < 9,780.38). Both models,
however, indicated that student mobility significantly and negatively impacted a student’s likelihood to graduate on time.

Research Question 3: Do Background Variables Contribute to On-Time Graduation?

Table 4.5 presents the results of the student-level investigation. With the addition of the student predictors, the cross-classified multiple-membership approach remained a better model fit than the first-school approach, as indicated by the lower deviance ($7,479.00 < 7,499.80$). The deviance for the cross-classified multiple-membership was smaller across all four previous models presented indicating that the multiple-membership mobility structure improved the fit of the model compared to the second approach, which considered only the first high school that mobile students attended.

The models supported previous research detailing the importance of key ninth-grade predictors (attendance, grades) and stronger academic background as related to on-time graduation. In all three approaches, a standard deviation increase in ninth-grade attendance improved a student’s odds of graduating on time by approximately 120 percent (OR = 2.233, 2.204, 2.200; $p < 0.001$). A standard deviation increase in ninth-grade GPA improved a student’s odds to graduate on time by 378 percent for the mobile-students-removed approach, 393 percent for the first-school approach, and 398 percent for the cross-classified multiple-membership approach (OR = 4.777, 4.929, 4.976; $p < 0.001$).

In addition to ninth-grade attendance and ninth-grade GPA, math proficiency and being female had positive log odds across the three approaches, suggesting that these predictors increased a student’s likelihood to graduate on time. However, students who were from families of low SES, received special education services, or were in the English language learner program
were less likely to graduate on time, as indicated by the negative log odds across the three approaches. After adding the student-level variables to the models, the effect of mobility in the multiple membership model was still significant (OR = 0.860, \( p < .05 \)), which, due to the coding of the ethnicity variables, can be interpreted as the reduced odds of on-time graduation for mobile students compared with the reference group (White students) who did not move. Mobile students would have decreased odds of on-time graduation of about 14 percent compared to their White peers who did not move.

Deleting mobile students from the model in the mobile-students-removed approach renders both female and low SES as not statistically significant at typical \( p \) values (\( p > 0.05 \)). Across all three approaches, African American and Hispanic backgrounds were not statistically significant at typical \( p \) values (\( p > 0.05 \)). The latter may be due to the low enrollment numbers of African American and Hispanic students within HIDOE schools.
<table>
<thead>
<tr>
<th></th>
<th>Mobile-Students-Removed Approach</th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Odds (Std. Error)</td>
<td>Odds Ratio</td>
<td>Sig.</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.627 (0.147)</td>
<td>1.872</td>
<td>0.000</td>
</tr>
<tr>
<td>Mobility</td>
<td>NA</td>
<td>-0.135</td>
<td>0.062</td>
</tr>
<tr>
<td>Ninth-Grade Attendance</td>
<td>0.803 (0.038)</td>
<td>2.233</td>
<td>0.000</td>
</tr>
<tr>
<td>Math Proficiency</td>
<td>0.318 (0.039)</td>
<td>1.375</td>
<td>0.000</td>
</tr>
<tr>
<td>Ninth-Grade GPA</td>
<td>1.564 (0.125)</td>
<td>4.777</td>
<td>0.000</td>
</tr>
<tr>
<td>Female</td>
<td>0.129 (0.068)</td>
<td>1.138</td>
<td>0.053</td>
</tr>
<tr>
<td>Low SES</td>
<td>-0.133 (0.069)</td>
<td>0.876</td>
<td>0.053</td>
</tr>
<tr>
<td>SPED</td>
<td>-0.339 (0.088)</td>
<td>0.712</td>
<td>0.000</td>
</tr>
<tr>
<td>ELL</td>
<td>-1.545 (0.125)</td>
<td>0.213</td>
<td>0.000</td>
</tr>
<tr>
<td>African American</td>
<td>-0.281 (0.236)</td>
<td>0.755</td>
<td>0.232</td>
</tr>
<tr>
<td>Asian/Pacific Islander</td>
<td>0.598 (0.101)</td>
<td>1.818</td>
<td>0.000</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.064 (0.155)</td>
<td>1.066</td>
<td>0.681</td>
</tr>
<tr>
<td>Native American</td>
<td>-0.780 (0.332)</td>
<td>0.458</td>
<td>0.019</td>
</tr>
</tbody>
</table>

**Random Effects**

<table>
<thead>
<tr>
<th></th>
<th>Variance (Std. Error)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.181 (0.054)</td>
<td></td>
<td>0.135 (0.041)</td>
<td>0.171 (0.050)</td>
</tr>
</tbody>
</table>

**Deviance**

<table>
<thead>
<tr>
<th></th>
<th>Mobile-Students-Removed Approach</th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6363.30</td>
<td>7499.80</td>
<td>7479.00</td>
</tr>
</tbody>
</table>
Research Question 4: Do Contextual Variables Affect On-Time Graduation?

In Table 4.6, the mobile-students-removed approach resulted in an almost 11 percent loss of data (i.e., mobile students). Removing the mobile students, therefore, diminished the power to detect effects should they exist in the population. This is shown in female ($p = 0.053$) and low SES ($p = 0.053$) not being significant at conventional $p$ levels ($p < 0.05$). In this case, eliminating the missing students likely resulted in Type II errors (not rejecting the null hypothesis of no relationship when it should be rejected) in this research approach compared with either the first-school approach or the multiple-membership approach.

In comparing the first-school approach and the multiple-membership approach, the standard errors were inflated for the school-level predictors in the latter approach, which is a primary reason for employing it. Leckie and Owen (2013) noted that assigning students to the first school they attend and then fitting a students-within-schools model of student on-time graduation will likely lead to the underestimation of the importance of schools and an overestimation of the importance of students as sources of variation in student attainment. More specifically, the first-school approach will likely result in underestimated standard errors for the predictor variables, particularly those measured at higher levels (Leckie, 2012).

In Table 4.6, all the standard errors are inflated in the multiple-membership approach compared to the first-school approach. This leads to a protection against the greater risk of making Type I errors (falsely rejecting the null hypothesis of no effect when it should not be rejected) and, therefore, incorrectly making inferences and drawing misleading conclusions about the relationships being studied. Two key differences regarding the effects of school predictors can be noted in Table 4.6. First, the effect of school size on students’ on-time
graduation was underestimated in the first-school approach compared with the multiple-
membership approach (i.e., OR = 0.874 to 0.860, respectively). This difference resulted in school
enrollment size not being a significant contextual predictor of on-time graduation in the first-
school approach ($p = 0.088$), whereas it was a significant predictor in the multiple-membership
modeling results ($p = 0.049$). This suggests that students in a school one standard deviation
larger in enrollment size than the sample average had reduced odds of approximately 14 percent
of students graduating on time compared with students in a school at the sample average size in
enrollment, holding other variables in the model constant.

Second, in Table 4.6, the effect of school-level math proficiency was not statistically
significant in the first-school model (OR = 1.115, $p = 0.106$) but was significant in the multiple-
membership model (OR = 1.169, $p = 0.016$). This suggested students in a school one standard
deviation above the sample mean in math proficiency had increased odds of graduating on time
of approximately 17 percent compared to peers in a school at the sample mean for school
proficiency, holding other variables in the model constant. This difference in school-level results
was likely due to the first-school approach only including information from one school and the
multiple-membership approach weighting the school effects for mobile students. The other two
school-level predictors (i.e., average teacher experience and parent perceptions of school
involvement in improvement) were unrelated to odds of graduating on time. For the student-level
factors in the model, the standard errors were basically the same in the first-school approach and
the multiple-membership approach.
<table>
<thead>
<tr>
<th></th>
<th>Mobile-Students-Removed Approach</th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Log Odds (Std. Error) Odds Ratio Sig.</td>
<td>Log Odds (Std. Error) Odds Ratio Sig.</td>
<td>Log Odds (Std. Error) Odds Ratio Sig.</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.568 (0.150) 1.765 0.000</td>
<td>0.544 (0.139) 1.723 0.000</td>
<td>0.541 (0.142) 1.178 0.000</td>
</tr>
<tr>
<td>School Math Proficiency</td>
<td>0.154 (0.076) 1.166 0.006</td>
<td>0.109 (0.068) 1.115 0.106</td>
<td>0.156 (0.072) 1.169 0.016</td>
</tr>
<tr>
<td>School Size</td>
<td>-0.199 (0.091) 0.820 0.029</td>
<td>-0.139 (0.081) 0.871 0.088</td>
<td>-0.168 (0.086) 0.845 0.049</td>
</tr>
<tr>
<td>Perception on school improvement</td>
<td>0.027 (0.082) 1.027 0.745</td>
<td>0.032 (0.074) 1.032 0.670</td>
<td>0.021 (0.067) 1.021 0.757</td>
</tr>
<tr>
<td>Teacher Experience</td>
<td>-0.093 (0.070) 0.911 0.183</td>
<td>-0.046 (0.065) 0.955 0.473</td>
<td>-0.051 (0.062) 0.950 0.409</td>
</tr>
<tr>
<td>Mobility</td>
<td>NA</td>
<td>-0.136 (0.073) 0.874 0.062</td>
<td>-0.153 (0.073) 0.858 0.035</td>
</tr>
<tr>
<td>Ninth-Grade Attendance</td>
<td>0.809 (0.038) 2.245 0.000</td>
<td>0.794 (0.035) 2.212 0.000</td>
<td>0.792 (0.035) 2.209 0.000</td>
</tr>
<tr>
<td>Math Proficiency</td>
<td>0.316 (0.039) 1.372 0.000</td>
<td>0.338 (0.036) 1.402 0.000</td>
<td>0.336 (0.036) 1.399 0.000</td>
</tr>
<tr>
<td>Ninth-Grade GPA</td>
<td>1.561 (0.126) 4.763 0.000</td>
<td>1.595 (0.121) 4.927 0.000</td>
<td>1.603 (0.121) 4.966 0.000</td>
</tr>
<tr>
<td>Female</td>
<td>0.130 (0.067) 1.138 0.051</td>
<td>0.160 (0.061) 1.173 0.009</td>
<td>0.158 (0.061) 1.173 0.009</td>
</tr>
<tr>
<td>Low SES</td>
<td>-0.131 (0.069) 0.878 0.057</td>
<td>-0.142 (0.063) 0.868 0.024</td>
<td>-0.135 (0.063) 0.873 0.033</td>
</tr>
<tr>
<td>SPED</td>
<td>-0.344 (0.088) 0.709 0.000</td>
<td>-0.301 (0.081) 0.740 0.000</td>
<td>-0.308 (0.081) 0.735 0.000</td>
</tr>
<tr>
<td>ELL</td>
<td>-1.541 (0.125) 0.214 0.000</td>
<td>-1.473 (0.116) 0.229 0.000</td>
<td>-1.456 (0.116) 0.233 0.000</td>
</tr>
<tr>
<td>African American</td>
<td>-0.263 (0.236) 0.769 0.265</td>
<td>-0.297 (0.218) 0.743 0.129</td>
<td>-0.283 (0.219) 0.754 0.196</td>
</tr>
<tr>
<td>Asian/Pacific Islander</td>
<td>0.624 (0.102) 1.866 0.000</td>
<td>0.503 (0.096) 1.654 0.000</td>
<td>0.519 (0.096) 1.681 0.000</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.077 (0.155) 1.080 0.621</td>
<td>0.066 (0.141) 1.068 0.643</td>
<td>0.051 (0.142) 1.052 0.719</td>
</tr>
<tr>
<td>Native American</td>
<td>-0.756 (0.332) 0.470 0.023</td>
<td>-0.703 (0.327) 0.495 0.032</td>
<td>-0.701 (0.328) 0.496 0.033</td>
</tr>
</tbody>
</table>
Table 4.6. (Continued) Student- and School-Level Model for the Three Approaches

<table>
<thead>
<tr>
<th>Mobile-Students-Removed Approach</th>
<th>First-School Approach</th>
<th>Cross-Classified Multiple-Membership Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Odds (Std. Error)</td>
<td>Odds Ratio</td>
<td>Sig.</td>
</tr>
<tr>
<td>Random Effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance</td>
<td>0.173</td>
<td>0.138</td>
</tr>
<tr>
<td>(0.053)</td>
<td>(0.043)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>Deviance</td>
<td>6355.68</td>
<td>7495.9</td>
</tr>
</tbody>
</table>

Analysis of Main Effects and Interactions

The primary comparisons between approaches in Models 2 through 4 included only main effects. Previous quantitative analyses on persistence often treated student background (e.g., ethnicity, family SES) as controls. By focusing on “average” effects, researchers may miss opportunities to provide more fine-grained analyses of how student-level variables intersect with student mobility in explaining on-time graduation. In addition, weighted school context indicators may moderate the effect of student mobility on graduation outcomes (Heck & Mahoe, 2006).

As an additional step, possible models for the multiple-membership approach were conducted by examining interactions between student-level variables and mobility and between school-level variables and mobility (i.e., cross-level interactions). This also contributes to ways in which the multiple-membership data structures might result in a more detailed set of results regarding possible school (and student background) impacts on the relationship between student mobility and on-time graduation in Research Question 4. An interaction can be interpreted as the amount of change in the logit of $y$ with respect to $x$ when $z$ (e.g., family SES) changes by one unit. More specifically, does the dependence of a student’s on-time graduation on whether the
student is mobile or not also depend on family SES? Non-significant interactions were removed from the final model presented.

Several relationships in Table 4.7 are of interest in furthering the understanding of student mobility and on-time graduation. First, the odds ratio describing the main effect of one student move versus staying in the same school was 0.741, suggesting a mobile student who moved once had reduced odds of graduating on time of about 26 percent compared with peers who did not move, holding other variables in the model constant. Due to the change in reference group from White to Asian/Pacific Islander, the mobility estimate can be interpreted as the impact of moving compared to Asian/Pacific Islander students who did not move (OR = 0.741, \( p < 0.001 \)). Students who moved would have reduced odds of on-time graduation of approximately 26 percent compared with Asian/Pacific Islander students who did not move. Second, in this model with main effects and interactions, using Asian/Pacific Islander students as the reference group for ethnicity changed the direction of log odds of graduating for other ethnic groups, which occurred because the Asian/Pacific Islander group had the highest graduation odds in the cohort data set. Third, the interactions involving mobility can be interpreted as the difference in odds regarding a second predictor (e.g., an English learner status) for a student graduating on time if the student moves one time versus stays in the same school. For language services, an English learner who moved had increased odds of graduating on time of about 78 percent compared to an English learner who did not move (OR = 1.784, \( p < 0.05 \)), holding other variables constant. A student one deviation above the sample mean in absences had reduced predicted odds of graduating on time by about 15 percent if the student moved (OR = 0.846, \( p < 0.05 \)) compared to a student with the same high number of absences who did not move.
Regarding ethnicity, a White student who moved once had odds of graduating on time about 2.3 times the odds of a White student who did not move (OR = 2.291, \( p < 0.01 \)).

Regarding school settings, for mobile students, attending a school one standard deviation larger in size than the average school was associated with decreased odds of graduating on time of about 18 percent (OR = 0.822, \( p < 0.05 \)) compared to students attending a school at the sample average for student enrollment. For students who attended a large school, however, moving appeared to be advantageous. More specifically, the odds of graduating on time were increased by about 1.24 times (OR = 1.241, \( p < 0.05 \)), or 24 percent, if a student moved once, compared with a peer in a similarly large school who did not move, holding other variables constant. These results imply if a student did not move, attending smaller school was beneficial in terms of graduating on time. If a student attended a large school, however, then moving once appeared to confer some noticeable advantage in terms of increased odds of on-time graduation compared to a student in the same type of setting who did not move.
Table 4.7. Multiple-Membership Model with Statistically Significant and Interactions

<table>
<thead>
<tr>
<th>Model Term</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>Sig.</th>
<th>Exp (Coefficient)</th>
<th>95% Confidence Interval for Exp (Coefficient)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.082</td>
<td>0.1177</td>
<td>0.000</td>
<td>2.950</td>
<td>2.342 - 3.715</td>
</tr>
<tr>
<td>Mobility</td>
<td>-0.300</td>
<td>0.0819</td>
<td>0.000</td>
<td>0.741</td>
<td>0.631 - 0.870</td>
</tr>
<tr>
<td>Gender (female)</td>
<td>0.156</td>
<td>0.0612</td>
<td>0.011</td>
<td>1.169</td>
<td>1.036 - 1.318</td>
</tr>
<tr>
<td>Low SES</td>
<td>-0.127</td>
<td>0.0636</td>
<td>0.045</td>
<td>0.880</td>
<td>0.777 - 0.997</td>
</tr>
<tr>
<td>Special education</td>
<td>-0.309</td>
<td>0.0808</td>
<td>0.000</td>
<td>0.734</td>
<td>0.626 - 0.860</td>
</tr>
<tr>
<td>English learner program</td>
<td>-1.540</td>
<td>0.1237</td>
<td>0.000</td>
<td>0.214</td>
<td>0.168 - 0.273</td>
</tr>
<tr>
<td>Ninth-Grade Attendance</td>
<td>0.838</td>
<td>0.0390</td>
<td>0.000</td>
<td>2.312</td>
<td>2.142 - 2.496</td>
</tr>
<tr>
<td>Math proficiency</td>
<td>0.336</td>
<td>0.0357</td>
<td>0.000</td>
<td>1.399</td>
<td>1.305 - 1.501</td>
</tr>
<tr>
<td>Hispanic¹</td>
<td>-0.455</td>
<td>0.1170</td>
<td>0.000</td>
<td>0.634</td>
<td>0.504 - 0.798</td>
</tr>
<tr>
<td>African¹</td>
<td>-0.804</td>
<td>0.2039</td>
<td>0.000</td>
<td>0.448</td>
<td>0.300 - 0.668</td>
</tr>
<tr>
<td>White¹</td>
<td>-0.607</td>
<td>0.1010</td>
<td>0.000</td>
<td>0.545</td>
<td>0.447 - 0.664</td>
</tr>
<tr>
<td>Native American¹</td>
<td>-1.231</td>
<td>0.3194</td>
<td>0.000</td>
<td>0.292</td>
<td>0.156 - 0.546</td>
</tr>
<tr>
<td>Ninth-Grade GPA</td>
<td>1.582</td>
<td>0.1215</td>
<td>0.000</td>
<td>4.865</td>
<td>3.834 - 6.173</td>
</tr>
<tr>
<td>School Math Proficiency</td>
<td>0.161</td>
<td>0.0719</td>
<td>0.025</td>
<td>1.175</td>
<td>1.020 - 1.352</td>
</tr>
<tr>
<td>School Size</td>
<td>-0.196</td>
<td>0.0866</td>
<td>0.024</td>
<td>0.822</td>
<td>0.694 - 0.974</td>
</tr>
<tr>
<td>Perception on School Improvement</td>
<td>0.013</td>
<td>0.0670</td>
<td>0.845</td>
<td>1.013</td>
<td>0.888 - 1.155</td>
</tr>
<tr>
<td>Teacher Experience</td>
<td>-0.057</td>
<td>0.0623</td>
<td>0.360</td>
<td>0.945</td>
<td>0.836 - 1.067</td>
</tr>
<tr>
<td>Mobility*English learner program</td>
<td>0.579</td>
<td>0.2728</td>
<td>0.034</td>
<td>1.784</td>
<td>1.045 - 3.045</td>
</tr>
<tr>
<td>Mobility*Ninth-Grade Attendance</td>
<td>-0.167</td>
<td>0.0649</td>
<td>0.010</td>
<td>0.846</td>
<td>0.745 - 0.961</td>
</tr>
<tr>
<td>Mobility*White</td>
<td>0.829</td>
<td>0.3041</td>
<td>0.006</td>
<td>2.291</td>
<td>1.262 - 4.157</td>
</tr>
<tr>
<td>Mobility*School Size</td>
<td>0.216</td>
<td>0.0869</td>
<td>0.013</td>
<td>1.241</td>
<td>1.046 - 1.471</td>
</tr>
</tbody>
</table>

Random Effect

| Variance                          | 0.165       | 0.0493     |

Random Effect

| Deviance                          | 7487.740    |

Probability distribution: Binomial
Link function: Logit
¹For ethnicity, Asian/Pacific Islander is the reference group.
Figure 4.1. Moderating effect of student mobility on the log odds of on-time graduation for students attending small and large schools.

Figure 4.1 provides a plot illustrating the odds of graduating on time for students attending a large school who moved (move = 1) versus did not move (move = 0). The average school enrollment (school enrollment = 0) serves as the point of reference. As the figure makes clear, moving to a small school (school enrollment = -1, -2, or -3) provided a relative disadvantage in terms of predicted log odds of graduating on time compared to not moving. In schools of increasing enrollment size (school enrollment = 1, 2, or 3), however, not moving was associated with an increasing disadvantage in terms of log odds of on-time graduation compared to moving.
Figure 4.2. Moderating effect of student mobility on the log odds of on-time graduation for students receiving English language services versus students not receiving services.

Figure 4.2 provides an illustration of the improved odds of on-time graduation for students receiving English language services (English Learner Program = 1). As the figure illustrates, for students not receiving English language services (English Learner Program = 0), moving schools decreased the odds of on-time graduation. For students receiving English language services, changing schools increased odds of on-time graduation compared to peers receiving English language services who did not move.
Figure 4.3 provides a visual summary of the moderating effect of mobility on average days attended during ninth grade. As summarized in the figure, for students of average attendance (ninth-grade attendance = 0) or lower (ninth-grade attendance = -1, -2, or -3), there is little effect of mobility on log odds of on-time graduation. For students with higher attendance (ninth-grade attendance = 1, 2, or 3), changing schools lowered the log odds of on-time graduation.
Finally, Figure 4.4 provides an illustration of moving versus not moving for White students in terms of on-time graduation. As the figure clarifies, for White students (White = 1), changing schools provided a considerable advantage in terms of log odds of on-time graduation compared to White students who did not move. Conversely, non-White students (White = 0) benefitted from remaining in the same school as opposed to moving.
Chapter 5. Discussion and Conclusion

Student mobility can adversely affect academic learning due to the disruption it causes in school-based social ties and academic routines (Center for Promise, 2015; Rumberger, 2003; Rumberger, 2015; Rumberger & Larson, 1998). This disruption can ultimately lead to students needing additional years in school to graduate or dropping out of school altogether. Students transfer to different schools for a variety of reasons, whether it is family-initiated, student-initiated, or school-initiated (Grim, 2019; Rumberger, 2015; Rumberger & Larson, 1998; Spencer, 2019; Swanson & Schneider, 1999; Voight et al., 2012). Regardless of the reason, student mobility negatively impacts student success.

In Hawai‘i, preliminary descriptive statistics revealed that one in ten high school students who were enrolled in a HIDOE high school at the start of their ninth-grade year transfer to another school at least once during their high school career. Of the 1,143 students who transferred school at least once, 323, or 28.3 percent, failed to graduate on time (see Table 3.2). Of the students who remained in the same school for all four years of this study, 15.9 percent failed to graduate on time, a difference of 12.4 percent. The gap is even greater for students who transferred more than once of whom 39.2 percent failed to graduate on time. Students who were mobile were more likely to be from a low SES family, experience low achievement based on math proficiency and ninth-grade GPA, and have more absences from school (see Table 3.4).

The goal of this study was to gain a better understanding of the effects of student mobility on graduation outcomes, which can lead to more appropriate supports and services for students who transfer schools in addition to the typical promotional transfers (elementary school to
middle school and middle school to high school). This study investigated four research questions:

1. Does the pattern of student likelihood to graduate on time vary across high schools in the state?
2. Does student mobility affect the likelihood of on-time graduation?
3. Do student background variables contribute to a student’s likelihood to graduate on time?
4. Net of student background variables, do school contextual variables affect the likelihood to graduate on time if the student is mobile during high school?

Table 5.1. Bronfenbrenner’s Ecological Model as the Study’s Framework

<table>
<thead>
<tr>
<th>Environmental Levels</th>
<th>Relation to Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1: Microsystem</td>
<td>Students’ likelihood to graduate on time is influenced by the students’ background.</td>
</tr>
<tr>
<td>Level 2: Mesosystem</td>
<td>Students’ likelihood to graduate on time is influenced by the school context and school processes.</td>
</tr>
<tr>
<td>Level 3: Exosystem</td>
<td>Factors outside of the school, such as those within the greater school community, may moderate student experiences in school and influence graduation outcomes.</td>
</tr>
<tr>
<td>Level 4: Macrosystem</td>
<td>The cultural context in which the student lives plays a role in shaping the student’s values and beliefs, which may in turn influence the student’s likelihood to graduate on time.</td>
</tr>
</tbody>
</table>

Bronfenbrenner’s ecological model served as the overall theoretical model underpinning this study, providing a way to incorporate the multiple school contexts that some students encounter during high school. This ecological model also provided a framework to define the major constructs of the conceptual model of this study (Figure 1.1). Bronfenbrenner’s model consists of four environmental levels, with each level impacting the development of each student
differently (Table 5.1). Within the microsystem, or the classroom in which students interact with teachers and peers, student-level factors such as student background (demographics, academic background) and student experiences (academic and social engagement) impact a student’s likelihood to graduate on time, as illustrated by the horizontal lines in the first level of the conceptual model. The mesosystem, which consists of the classroom, the school, and the student’s home, integrates into the model the school-related factors that influence graduation outcomes and student mobility. These school-related factors include school context (student composition and stability, school structure) and school processes (academic and social support), represented by the diagonal lines in the conceptual model. Factors outside of the classroom and school that do not directly involve the student but do indirectly influence graduation outcomes, such as the socioeconomic status of the neighborhood in which a student lives, are included in the exosystem. Finally, the macrosystem, which this study did not delve into, involves the larger cultural context (societal beliefs, cultural norms, ideologies, policies, laws) that may indirectly influence graduation outcomes. Per Bronfenbrenner’s model, the environment, social interaction, and time play essential roles in a student’s development. Students who move from one school to another experience changes in the environment, social interaction, and time, which may, in turn, impact their academic and social development and, ultimately, their graduation outcomes.

Discussion of the Findings

The challenge with examining the effects of student mobility on on-time graduation is properly incorporating student mobility in a data analysis model. While previous research explored the impact of student mobility on student performance and a negative relationship was found, in most extant studies, researchers were not able to estimate the school-level effects of
attending multiple schools directly into the model investigated (e.g., Goldschmidt & Wang, 1999; Grim, 2019; Heck & Mahoe, 2006; Metzger et al., 2015; Norbury et al., 2012; Wright, 1999). To provide a more thorough examination of on-time graduation within a large student cohort, this study utilized three multilevel approaches – two common and one underutilized – to estimate the effects of student mobility on graduation outcomes, controlling for common student and school-level predictors identified in previous research. One common approach, the mobile-students-removed approach (e.g., McRoach et al., 2006; Wright, 1999), addressed the mobility problem in examining student graduation outcomes by simply eliminating mobile students from the data set, leaving only students who remained in the same school throughout the four years of high school. The first-school approach attributed only the characteristics of the first school in which the mobile students were enrolled to the impact on graduation outcomes. Unfortunately, neither of these previous approaches for studying on-time graduation was able to incorporate student mobility properly into the proposed multilevel model, as they failed to attribute the factors from all schools that mobile students attended to on-time graduation. The third approach, the cross-classified multiple-membership approach, merges the data from the high schools in which the mobile students were enrolled into one weighted value for the school-level predictors. This allows for a more accurate incorporation of student mobility and school context effects into the research model investigated (e.g., Chung, & Beretvas, 2012; Leckie, 2009). Most existing studies using multiple-membership data structures, however, have been directed at presenting the method rather than employing it to contribute to substantive findings (Leroux, 2019).
The results of the study contribute to both the substantive findings on student mobility and on-time graduation as well as the technical merits of utilizing a multiple-membership data structure in multilevel analysis of student and school effects regarding on-time graduation.

**Substantive Findings**

Because the cross-classified multiple-membership approach proved to be a better model fit than the mobile-students-removed and first-school approaches, the results are discussed primarily in terms of the multiple-membership model findings. The results of the final main-effects model summarized in Table 4.6 revealed that the on-time graduation rate varied across HIDOE high schools and student mobility did significantly impact graduation outcomes, decreasing a student’s odds of graduating on time by approximately 14 percent, after controlling for student- and school-level predictors. Student predictors, such as low SES, special education, and English learner, and school predictors also contributed to decreased odds of on-time graduation. Ninth-grade attendance and individual proficiency in math increased students’ odds of on-time graduation. The pattern of student-level predictors explaining on-time graduation versus still being in school or leaving school early was consistent with previous research on high school persistence (e.g., Allensworth & Easton, 2007; Heck & Mahoe, 2006; Lee & Burkam, 2003; South et al., 2007). These findings were also consistent with limited previous multiple-membership research which noted that the main effects of student-level demographics on outcomes investigated tended to be fairly similar across various approaches (Chung & Beretvas, 2012; Durrant, Vassallo, & Smith, 2018).

At the school level, the multiple-membership results indicated that aggregated statewide math assessment performance positively contributed to a student’s likelihood to graduate on
time. For students attending schools with stronger math assessment results, odds of on-time
graduation were increased by nearly 17 percent compared with students attending schools at the
sample average for math proficiency, holding other variables in the model constant. In contrast,
school size negatively impacted a mobile student’s graduation outcome. The larger the school,
the greater the impact—that is, for students attending a school larger in enrollment by one-
standard deviation, the effect was a reduction in odds of graduating of nearly 15 percent
compared with peers attending schools at the sample average, holding other variables in the
model constant. Importantly, neither result was statistically significant in either the mobile-
students-removed or first-school approaches. The other school-level covariates investigated
during the model-building process were not statistically significant (e.g., teacher experience,
parent perceptions of school improvement, teacher stability).

With respect to the last research question investigated regarding the net effects of
examining multiple school contexts in contributing to graduation outcomes, in one simultaneous
model, the multiple-membership approach utilized in this study facilitated a more accurate
consideration of the effects of “multiple environments” on educational attainment that was
identified as a challenge in previous research (La Torre et al., 2019; Leckie, 2009; Leroux,
2019). The last set of analyses conducted in Chapter 4 examined possible interactions between
student-level variables and mobility and between school-level variables and mobility (i.e., cross-
level interactions) as summarized in the multiple-membership model. Researchers noted these
types of within-level and cross-level interactions were often not investigated in previous research
on student persistence (e.g., Heck & Mahoe, 2006; Lee & Burkam, 2003; Pollock, 2004). Four
statistically significant interactions were retained (see Table 4.7).
Regarding school context (see Figure 4.1), a closer look at the effect of school size on student on-time graduation revealed for students who did not move, attending a small school provided a clear advantage in terms of on-time graduation. For students who attended large schools, however, changing schools considerably reduced the negative impact on the log odds of graduating on time. More specifically, for students attending a school one-standard deviation in enrollment size above the sample average, moving increased the odds of graduating on time by nearly 25 percent, compared with a peer in the same school setting who did not move. This more fine-grained analysis indicated that as school enrollment increased, the likelihood of graduating on time for non-mobile students also decreased, once again indicating that non-mobile students were more successful in smaller schools. The opposite can be said about mobile students who were in larger schools; that is, moving appeared to provide benefits to on-time graduation compared with students who did not move, although the possible reasons are unclear from these data.

At the student level, the interaction multiple-membership model revealed a more detailed set of substantive findings regarding the overall “main” negative effect of student mobility and on-time graduation. For example, the interaction results indicated that students receiving English language instruction benefited by moving in terms of increased odds of on-time graduation compared to their peers who did not move (Figure 4.2). More specifically, for English language learners, moving increased the odds of on-time graduation by approximately 78 percent compared with their English language learning peers who did not move, controlling for other variables in the model. Regarding mobility and graduation, for students with higher ninth-grade attendance, moving tended to decrease the odds of on-time graduation compared with their peers.
with higher attendance who did not move (Figure 4.3). Finally, for White students, changing schools conferred considerable advantage (nearly 130%) in terms of on-time graduation compared to their White peers who did not move (Figure 4.4).

**Technical Contribution**

The cross-classified multiple-membership approach proved to be a better model fit than the mobile-students-removed and first-school approaches in determining the impact of student mobility on graduation outcomes. More specifically, the multiple-membership approach fit the data better in terms of model deviance than the first-school approach at each step of the model-building process. The pattern of school-level findings in the main-effects model and the subsequent pattern of significant interactions after examining possible interactions support the limited previous research noting that ignoring multiple-membership structures in multilevel models led to no substantial effects on level-1 (i.e., student level) parameters; however, ignoring the multiple-membership structure can produce bias in estimating parameters and variances at group levels (Chung & Beretvas, 2012; Durrant et al., 2018; Moerbeek, 2004). Aside from the substantive merits of the approach, the multiple-membership approach facilitates the incorporation of aggregated, weighted effects of the school-level predictors comprising the schools in which a mobile student was enrolled into one weighted data point for each school predictor for each individual student, resulting in more accurate estimates of multiple school effects on student on-time graduation.

To explore this point further, Figure 4.1 indicated that the mobility-graduation effect also depended on levels of school enrollment size in the multiple membership model. In that figure, we can observe that in small schools (i.e., below the sample average of 0), “not moving” was an
advantage in terms of on-time graduation. However, enrollment in larger schools resulted in the advantage of being a non-mobile student disappearing. For non-mobile students, being in a larger school implied there was an increasing “disadvantage” associated with not moving rather than moving. Thus, the idea of the “significant” interaction means that the relationship involving student mobility and on-time graduation also depends on features of the school-level environment – in this case, school enrollment size. The facility in being able to incorporate multiple school environments in estimates of school effects represents a technical advancement in understanding school effects on student outcomes. The technical capability of multiple membership data structures to incorporate multiple schools into the analysis is consistent with Bronfenbrenner’s theory suggesting the possibility of multiple environments affecting student outcomes in diverse manners. In this case, the analysis indicated both statistically significant direct (main effect) and indirect (through student mobility) ways in which school enrollment size impacted student on-time graduation.

In addition to the direct and moderating effects of school enrollment size, the achievement context of the school was also a statistically significant predictor on on-time graduation in the multiple-membership model. These findings were consistent with previous research noting academic features of school environments were related to graduation outcomes (e.g., Alspaugh, 1998; Bryk & Thum, 1989; Heck & Mahoe, 2006; Lee & Burkam, 2003; Rumberger & Thomas, 2000), even without directly incorporating student mobility through utilizing a multiple-membership data structure.
**Limitations**

Although this study determined that student mobility does impact graduation outcomes, there are several limitations to consider in assessing its findings. First, the study only considered students who were enrolled in HIDOE schools at the beginning of their initial ninth-grade year. Students who transferred into the HIDOE public school system after the beginning of their ninth-grade year were not included. These students would have also been considered as mobile, with their entrance into a HIDOE high school as the first non-promotional move.

Second, due to data limitations, the study only considered the high schools in which students were enrolled at the beginning of each school year and assumed the students were enrolled in these schools for the entire school year. It, therefore, did not account for the multiple moves a student might have made during a single school year nor the few months a student may have been enrolled in a different school during a particular school year. For example, a student may have transferred from School A to School B midway through ninth grade and remained at School B for the entire tenth-grade year, but the data would have showed the student as being at each school for an equal amount of time – School A for ninth grade and School B for tenth grade.

Third, this study did not consider when students transferred from one high school to another. As previous research suggested, students who transferred during either grade 9 or 10 and remained in the same school during grades 11 and 12 were more likely to persist through high school and graduate than students who transferred later in their high school career (Swanson & Schneider, 1999). The grade level in which students transfer school may impact graduation outcomes differently.
Fourth, this study could not disaggregate further the Asian/Pacific Islander subgroup. This is the largest subgroup in Hawai‘i, which includes Native Hawaiian and Filipino, both of which are the largest subgroups alone. Together, the Asian/Pacific Islander category had the highest on-time graduation rate among the subgroups considered within the study, controlling for student background and school variables. Yet, it is likely that further disaggregation of the data would have yielded considerable differences among the subgroups comprising this category. It would benefit Hawai‘i’s schools if future studies disaggregated the Asian/Pacific Islander subgroup further to determine the impact of student mobility of a student population more reflective of HIDOE’s student enrollment.

Fifth, although this study determined that mobility decreased a student’s likelihood to graduate on time, it was not possible to fully disaggregate the mobility data into the reasons for the moves. A considerable number of students moved out of the system (approximately 11% of the original cohort). Some of those students moved to private schools or left the state. Of the remaining cohort, another 10.5 percent changed schools within the public school system. Further research should be conducted to identify the extent to which each type of student move (e.g., seek a better school, disciplinary transfer, residential, change in family status, public to private school, public to charter school) may impact the graduation outcomes of high school students and graduation rates of high schools.

Addressing these limitations in future research (i.e., including students who transferred into the HIDOE public school system after ninth grade, tracking the within-year moves as well as the grade in which the move takes place more accurately, disaggregating the Asian/Pacific Islander subgroup, and understanding the reasons for school moves) should provide a clearer
picture of student mobility across the schools in Hawai‘i. This will, in turn, provide a more comprehensive look at the impact of mobility on graduation outcomes and inform the supports needed to facilitate student success.

**Conclusion**

This study highlights the value of the cross-classified multiple-membership model. This model allows for the inclusion of school-level predictors in a manner that more accurately attributes the school characteristics to the student. Having the ability to attribute to each individual the characteristics of each higher-level unit to which the individual belongs based on the duration for which the individual belonged to each unit allows for a more thorough and accurate analysis of the study’s outcomes. The utilization of the cross-classified multiple-membership model provided a more nuanced understanding of how student mobility, which leads to multiple configurations of students within schools, impacts graduation outcomes.

Student mobility hinders student success in school. Students who are mobile are more susceptible to poor academic performance and less likely to graduate on time than non-mobile students. Mobile students experience a disruption in their social relationships with their peers and the adults on campus, having to build new social and support networks amongst those who have already established relationships and social circles. They also experience a disruption in their academic routines, having to adjust to a new learning environment, new classroom rituals, and new teacher expectations, all of which their peers have already routinized. Without the proper social and academic supports, mobile students are at risk of disengaging in school, which may, in turn, lead them to not fulfill the graduation requirements on time or drop out of school altogether. Knowing that school attendance and math proficiency positively impact on-time graduation for
mobile students, increasing student engagement by offering school programs that meet the diverse needs of students and providing the appropriate academic and social-emotional supports may encourage students to persist through high school. More importantly, providing transitional supports to help students acclimate to the new school may mitigate the negative effects of student mobility.

While student transition is a priority for HIDOE, more focused supports may be needed for students who make non-promotional changes during high school. Identifying the contributing factors that impact graduation outcomes of mobile students may clarify the supports needed. Mobile students are not only at risk of not graduating on time or at all, but also at risk of experiencing subsequent challenges such as unemployment and poverty. Thus, increasing the likelihood of graduating on time for mobile students is critical in facilitating their success in school and beyond. Further research on the impact of student mobility on graduation outcomes addressing the aforementioned limitations would better inform school improvement efforts and the supports and services provided to increase student achievement and persistence.
References


