

REDEFINING THE GAP: CONSIDERING OPPORTUNITY FACTORS ON ACADEMIC  
SUCCESS OUTCOMES FOR MONTANA STUDENTS

by

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## DEDICATION

To my husband, Tyler, you are the reason I began this graduate journey six years ago, and you are the reason I am able to complete it now. Your unwavering support has been the foundation of every little step, and your belief in me has given me the space for every big breath. Thank you for encouraging me when I doubted myself and for always reminding me of the strength within. This dissertation is as much yours as it is mine—a testament to the patience, understanding, and joy you brought to every long night and early morning. I am forever grateful for the sacrifices you made to make this possible. You are still my greatest adventure.

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## ABSTRACT

This study examines educational inequity among Montana high school students by investigating the influence of social location (gender, race, and socioeconomic class) and opportunity factors (student mobility and poverty) on academic achievement and completion. Using a robust multilevel modeling approach, this research analyzes longitudinal student and school data to address four primary questions: differences in academic success based on students' social locations, and the impact of individual and school-level factors on achievement and graduation likelihood. Key findings reveal that high-poverty male and American Indian/Alaskan Native (AIAN) students face compounded barriers to academic success, with significant disparities in both ACT performance and graduation rates. Analysis of the within-group sample of AIAN students highlights the role of mobility and poverty as critical opportunity factors, underscoring the distinct challenges faced by Native students, particularly those attending on-reservation schools. The study's results contribute to the understanding of how intersecting social locations impact educational outcomes and challenge the traditional "achievement gap" framework. Recommendations include expanding Montana's educational reporting to address nuanced disparities across social locations and implementing support systems tailored to high-poverty and mobile students. This research emphasizes the need for data-driven policy reform to promote equity and address systemic barriers within Montana's educational landscape. While this study's findings show a statistically negative relationship between mobility and academic outcomes, they should be interpreted with care, as mobility encompasses complex experiences and cannot be fully understood through quantitative data alone. Recognizing mobility as an opportunity factor captures this nuance, as mobility may present significant challenges for some students while providing meaningful opportunities for others, such as a move to a more stable home environment. This study highlights the need for both quantitative and qualitative approaches to truly unearth the multifaceted role that mobility plays in Montana, reminding us that interpreting mobility solely as a barrier risks overlooking its potential as a positive force in students' lives.

## CHAPTER ONE

## INTRODUCTION

Historic responses to various adopted “achievement gaps” between groups of students too often insinuates the problem resides with the students, and more specifically, students of color. There is a culture of avoidance in placing acute responsibility on the systems and structures, rather than a culture which seeks to challenge the common deficit model (Chambers, 2009). In the state of Montana, the culture of avoidance and commonly accepted “achievement gap” refers to the differences in academic outcomes between Native students and their non-Native peers, where the bi-annual *American Indian Student Achievement Report* (OPI, 2022; 2020a; 2018) produced by the Montana Office of Public Instruction (OPI) has become synonymous with simply the “Achievement Gap Report” implying Native student deficit.

In this way, the acknowledged Montana “achievement gap” has produced severe limitations on how we understand student success in our state as the report only exposes differences between two sub-groups of students (Native and non-Native) without consideration for other intersecting social locations such as expanding race/ethnicity away from a binary perspective, gender, or individual and school-level poverty. In addition, the report focuses on only two academic outcomes— academic achievement measured using standardized test scores and academic completion measured using cohort graduation rates— to fully measure differences in student success without accounting for the extensive variety of factors impacting those academic outcomes such as student mobility, student poverty, student homelessness, and more.

Such data of the Montana “achievement gap” continues to circulate through state and local-level policy with the aim of informing the decision making of leaders to better serve

students. And yet, the data is incomplete providing our leaders, and ultimately our students, with a data story that only scratches the surface of what needs exist to equitably provide access to academic success for all students. Not only does the literature and reporting around the Montana “achievement gap” need to be redefined to include consideration for all K-12 students, but direct consideration for the variety of factors impacting academic access must participate as a central understanding of how students participate in their school experience, perhaps one of the most prevalent of these factors being student mobility patterns, especially when considering spatially informed student social context such student-level and school-level poverty.

Longitudinal Montana data reveals that Native students have significantly higher rates of mobility compared to their non-Native peers (GEMS, 2023c) where almost 50 percent of Montana Native students attend more than one school system throughout the duration of their school experience in a three-year time period. And yet this factor (and others of similar impact such as student homelessness) impacting opportunity to academic access is not aligned to the data revealed in these biennial achievement reports. We miss the larger picture as decision makers and leaders. When we continue to look at “achievement gaps” we interpret the solution as investing robust response toward achievement measures. When consideration for opportunity factors (such as mobility or poverty) are part of the conversation, we expose solutions for generating consistent access for students. Our state can no longer afford achievement-based band aid solutions. It is time to expand data analysis and redefine our understanding of the Montana “achievement gap” between Native and non-Native students to academic access for all K-12. This shift is critical not only to broaden our understanding of educational disparity but also to foster a more comprehensive approach that addresses root causes rather than symptoms. A

redefined focus on opportunity factors enables leaders to make informed, targeted decisions that address underlying inequities across all student groups.

### Statement of Problem

Acknowledged academic “achievement gaps” in education—or visible disparities between groups of students that history has repeatedly placed in distinct advantaged and disadvantaged groups (e.g. racial minorities) among various academic outcome measures (Valant & Newark, 2016)—continue as a major practice, policy and research concern across the field of education (Carey, 2014; Shukla et al., 2021). In particular for the state of Montana, the biennial *American Indian Student Achievement Report* has become synonymous with simply the “Achievement Gap Report” highlighting differences in academic outcomes between Native students and their non-Native peers. Dependence on “achievement gap” analysis avoids placing responsibility on the structure itself and instead functions within a student deficit model (Chambers, 2009), where in Montana, this implies Native student deficit.

In turn, the perception of the “achievement gap” is left unacknowledged by the abundance of inequalities which impact student performance (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010), such as student mobility (Astone and McLanahan, 1994; Crowder and South, 2003; Ingersoll et al., 1989; McLanahan & Sandefur, 1994; Straits, 1987; Swanson & Schneider, 1999, Teachman et al., 1996) and poverty (NCES, 2013; Shakeel & Peterson, 2022). In Montana, Native student mobility between school systems is significantly more pronounced than among their non-Native peers (GEMS, 2023c). It is imperative for research to examine the social, economic, and educational experiences of students and how the factors impacting student academic experiences (i.e. student mobility, poverty) impacts the disparity between student

groups. Continued analysis of “achievement gaps” in education crave a better understanding of demographic and experience factors of students to reveal the impact of intersecting inequalities.

### Purpose of Study

The purpose of this study, as part of an emerging field of QuantCrit,– or quantitative methods aligned with Critical Race Theory (Solórzano and Ornelas, 2002; Solórzano and Villalpando 1998; Solórzano and Yasso 2002)– seeks to utilize intersectionality within quantitative methods (Crenshaw, 1991; Fine, 1991; Hancock, 2013; LaVeist, 1994; McCall, 2001, 2005; Museus & Griffin, 2011; Solórzano et al., 2005; Villalpando 2003, 2004; Zuberi, 2001) to better understand the relational impact of race-gender-class gaps on academic success in K-12 Montana education. By crafting extensive combinations between race, gender and class this study is able to orient grouped social locations between these identities to better understand the impact of intersecting inequalities. Based on the work of López et al. (2018) this study will examine “achievement gaps” by isolating the linear combinations of marginal effects for completion (graduation) outcomes and achievement (ACT composite scores) at Montana public high schools for 28 distinct social locations. These social locations are based on race, gender and class, where the reference group is white, low-level poverty female students.

Further robust multilevel model (MLM) building is used to examine the impact of opportunity factors on standard metrics of academic success (achievement and completion). Most specifically, this study explores the impact of student mobility,—or when students change schools either within the academic year or between academic years (Rumberger, 2015)— student poverty, and school poverty as three prevalent opportunity factors impacting access to academic success. Robust MLM linear and logistic regression models are utilized to explore these

opportunity factors on academic outcomes of academic achievement and academic completion. Education data are inherently clustered as students are nested within schools. MLM (Raudenbush & Bryk, 2002) is the traditional statistical approach for adjusting for clustering of students within schools. Using the exploratory school-level SIDE poverty metrics for Montana public high schools (NCES, 2021a), the study will investigate the impact of student mobility on academic achievement in relation to school and student poverty.

### Research Questions

1. Are there observable differences by academic achievement based on students' social location orientation (gender, race, class)?
2. Are there observable differences by academic completion based on students' social location orientation (gender, race, class)?
3. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic achievement?
4. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic completion?

### Significance of Study

The current Montana “achievement gap” literature and data reports focus on highlighting student academic achievement and completion differences between Native and non-Native students, and in this way expect only to find a race gap to explain such differences. QuantCrit

aligned with intersectional methodology transforms the question from “what’s more important: race, gender, class?” to “how can we examine unique constellations of race, gender, class social location as categories of experience in a given sociohistorical and political economic context?” (López et al., 2018, p. 181). The goal becomes focused on how to reveal educational and social inequalities for race-gender-class social locations, rather than strictly “achievement gap” efforts focused on race, to “deracialize statistics” (Zuberi, 2001) and illuminate gaps “making the invisible visible” (López et al., 2018) or otherwise exploring and revealing the inequalities that conventionally remain invisible for students.

Current “achievement gap” literature and data reports in Montana also insufficiently consider the impact of various student experience factors impacting access to academic achievement and completion. One prevalent experience factor on both academic achievement (Hanusheck et al., 2004; Ingersoll et al., 1989; Rumberger, 2015; Schwartz, et al., 2009; South et al., 2007; Xu et al., 2009) and completion (Astone and McLanahan, 1994; Crowder and South, 2003; McLanahan & Sandefur, 1994; Straits, 1987; Swanson & Schneider, 1999, Teachman et al., 1996) is that of student mobility. Similarly, both student-level (Barton & Coley, 2009; Burkam, 2002; Gottlieb, 2002; Levy & Duncan, 2000; Palardy, 2002; Rowen et al., 2004; Rumberger & Smith et al., 1997) and school-level (Anderson et al., 1992; Andrews et al., 2003; Berliner, 2009; Gottlieb, 2002; Kahlenberg, 2004; Rusk, 2002; Tschinkel, 1999) poverty influence students’ academic achievement (NCES, 2013; Shakeel & Peterson, 2022). By layering understanding of students’ experience with their social context a more thorough data story may ensue for the Montana “achievement gap” literature, ultimately informing the decision making processes to support our students. While other student experience factors (e.g. student

homelessness) are needed in the continuation of developing a robust understanding of “achievement gaps,” accessing student mobility with students’ social context, including individual and school-level poverty, serves as a major first step in articulating the data story of educational inequity that currently exists in Montana.

### Theoretical/Conceptual Framework

The theoretical underpinnings of this study emerge from the framework of Critical Race Theory (CRT) committing to progress through social justice outcome intentions (Bell, 1976; Crenshaw, 1991). In particular and aligned to the intentions of this study, such outcomes acknowledge the tangible structural inequalities of racialized “achievement gaps” and the need for analysis and policy to dismantle the cyclical culture and systemic blindness to student deficit discourse. While “achievement gap” culture has become the norm over the past two decades, the experiences of students within their academic places and spaces are defined by more than their graduation and ACT outcomes. Rather, resisting a common acceptance of student deficit perspective, reporting and policy informed by “achievement gap” measures must expose the “opportunity gaps” which persist. In giving voice to the opportunity factors in “achievement gap” reporting, perhaps what may ensue for policy and leadership are data stories more acutely informed to the experiences of students directly impacting academic outcomes. In doing so, decision making can more closely examine attributes and supports to academic success across student experiences rather than simply continuing to paint the picture of disparity in outcomes between student groups.

Underneath the umbrella of CRT, QuantCrit and quantitative intersectionality projects are one emerging approach for unveiling inequalities in our education system for students

(Solórzano & Ornelas, 2002; Solórzano & Villalpando 1998; Solórzano & Yasso 2002) by providing quantitative strategy for investigating the relational impact of race-gender-class gaps in education. Educational inequity is observed in the continuation of students from the most privileged backgrounds continuing to dominate educational opportunities, and is a significant enduring social problem that continues to be examined extensively in social science research (McMaster & Cook, 2019). Substantial policy and funds have been dedicated to addressing these existing inequalities with no “straightforward solutions” (p. 271). QuantCrit and quantitative intersectionality projects embrace a “conceptual model for the sedimentation of intersecting inequalities” (López et al., 2018, p. 200). Aligned to the intentions of this study, utilizing social locations and incorporating opportunity factors rather than simply investigating achievement outcomes, this study seeks to “deracialize statistics” (Zuberi, 2008) by deracializing the “achievement gap.”

As another branch of CRT, Critical Race Spatial Analysis (CRSA) is an explanatory framework and methodological approach that accounts for the role of race and racism in geographic and social spaces. Identifying racism across geographic contexts, CRSA seeks to spatially analyze the structural and institutional factors associated with power and place (Solórzano & Velez, 2016). Aligned to the intentions of this study, the framework of CRSA is poignant considering the ways in which poverty and mobility are structurally and spatially informed by power and place. Dismantling and deracializing the Montana “achievement gap” will take more than a quantitative study exploring the impact of social locations, poverty and mobility on academic outcomes. However, far too long Montana “achievement gap” policy and reporting has let binary achievement measure data speak for itself, unveiling a racist data story

that Native students are ill-equipped to measure up to their non-Native peers. In the ways that QuantCrit refuse to let data speak for itself and in the ways CRSA refuses to let maps speak for themselves, the Montana “achievement gap” must welcome the voices of data which speak to opportunities in academic access for all students. In this study, these data are spatially informed further articulating that the places of schools contribute to unjust geographies and are central to the intersections of space, power and knowledge (Morrison et al., 2017, Soja, 2010).

### Research Design

This study is a nonexperimental research design that involves analysis of longitudinal student-level and school-level data following a single cohort of Montana high school students from their 11th to 12th grade years in 2018 and 2019. The research questions seek to understand the relationships and impact of student experience and poverty on academic achievement and completion. This study utilizes data collected through the Montana AIM Student Information System. AIM is a system designed to collect demographic, enrollment, program participation, and assessment data on every student enrolled in a Montana public school and is informed by Montana school systems’ local level Student Information Systems (e.g. Infinite Campus, Power School, etc.). In addition, this study also explores use of a new school-level poverty metric from the National Center of Education Statistics’ Spatially Interpolated Demographic Estimates (SIDE) Project for Montana high schools.

This study aligns to existing “achievement gap” reporting in Montana by focusing on academic achievement (standardized test scores) and academic completion (high school graduation/dropout) as the outcomes. Focused only on high school students in this study, academic achievement is measured using ACT composite scores. The factors of poverty and

mobility stressed in this study focus on illuminating where current “achievement gap” reporting is inadequate by exploring these as opportunity factors. Poverty is captured in two ways: (1) student-level poverty as a categorical variable using National School Lunch Program data for students qualifying for Free and Reduced Lunch, and (2) school-level poverty as a continuous variable using SIDE estimates. Mobility is captured as non-structural student-level mobility in 2019 where the frequency of mobility represents unique school system enrollments.

The examination of students’ social locations replicates the work of López et al (2018) which are based on race-ethnicity (federal race/ethnicity codes; categorical), gender (male/female; binary) and student poverty (free and reduced price lunch participation; binary), where the reference group is white, low-level poverty, female students. The categorical variable for race in this study uses the five federal categories, as well as categories for students who identify as Hispanic and Multiracial. The binary variable for student-level poverty in this study uses free and reduced price lunch (FRPL), in which case a student-level variable is transformed by acknowledging students who receive free or reduced lunch as high-level poverty and students who are not eligible as low-level poverty.

### Data Analysis

First, descriptive statistics are used to thoroughly describe the dataset and the context of these Montana students. Based on the work of López et al (2018), saturated regression models are then used to explore the social locations where race, gender, and class serve as proxies for students experience in regards to high school graduation and achievement on the ACT. In this way, the model uses 28 social locations, or unique groups that saturate the model and attempt to serve as distinct categories of experience within the model. The intent of utilizing these models is

to show how these distinct social locations intersect with one another. McCall (2005) identifies this exploration as exploring ‘intracategorical intersectionality,’ or within-group differences, and ‘intercategorical intersectionality,’ or between-group differences.

Second, robust multilevel regression models (MLMs) were employed to examine the effects of poverty and student mobility among a within-group sample of Native-only students. These non-saturated models accounted for both academic achievement and academic completion as outcome variables. For academic achievement, linear MLM regression was utilized, while logistic MLM regression was applied for academic completion. In both sets of models, appropriate student- and school-level controls were incorporated to account for factors influencing the outcomes. The robust MLM approach was selected as a more suitable alternative to standard linear or logistic regression, as it accounts for the nested structure of students within schools. This modeling strategy addresses the impact of opportunity factors on the outcomes by considering school-level differences using random intercept models.

### Operational Definitions

#### Educational Inequality

Educational inequity is evident in the cycle where students from the most privileged backgrounds consistently dominate educational opportunities. This persistent issue remains a significant social problem and continues to be a major focus in social science research (McMaster & Cook, 2019). Vertical educational inequities are those that “separate individuals in a hierarchical fashion according to the amount or level of education completed,” while horizontal inequities “relate to differences within a given level of education such as degree subjects” (p. 272).

### Achievement Gap(s)

“Achievement gaps” in education refer to the differences in academic outcomes between historically advantaged and disadvantaged groups of students (Valant & Newark, 2016) and is always placed in quotes in this study acknowledging the cries of stakeholders in Montana to refer to these disparities instead as “opportunity gaps” (Clausen et al., 2020). In the state of Montana, the commonly accepted “achievement gap” refers to the differences in academic outcomes between Native students and their non-Native peers. However, the perception of the “achievement gap” is left unacknowledged by the abundance of inequalities which impact student performance (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010). Acknowledging that the academic “achievement gap” is a product of the “receivment gap” (Chambers, 2009) or “opportunity gap” (Clausen et al., 2020) is informed by the theoretical frameworks of CRT (Dixson and Lynn, 2013, 3; Gillborn 2005, 2006a, 2006b, 2008) and intersectionality (McCall, 2001) which guides research to examine the social, economic, and educational experiences of students and how the factors impacting the receivment/opportunity gap impact the disparity between student groups.

### Intersectionality

As a central tenant of CRT, intersectionality functions as a lens to examine the “interlocking disparities in education” to critique and address “the problem of educational inequality” (McMaster & Cook, 2019, p. 272). Intersectionality acknowledges that social categories such as gender, race, ethnicity, and class are interrelated, impacting one’s experience “at the interface between these categories” (p. 273). Intersectionality is a tool for social science research (McMaster & Cook, 2019) used to deconstruct social categories such as gender, race

and class (anti-categorical complexity), to analyze differences and similarities within social categories (intra-categorical complexity) or to focus on multiple, intersecting inequalities between social categories (inter-categorical complexity) (McCall, 2005).

### Social Location

Based on the work of López et al. (2018) intersectionality can be examined through quantitative methods to better understand the relational impact of race-gender-class gaps on the educational experiences of students. It is through “unique constellations of race, gender, [and] class social location[s] as categories of experience in a given sociohistorical and political economic context” (p. 181) that educational inequity for groups of students can be revealed. Analysis of these intersections by social location not only “interrogate configurations of inequality” (McCall, 2001, p. 6), but participate as a step toward “deracialized statistics” (Zuberi, 2001).

### American Indian, Native American, and Montana Indigenous Peoples

*American Indian* and *Indigenous/Native* are not used interchangeably in this study to recognize continued oppression through naming in our American institutions. *American Indian* is used when referring to various political uses and context such as the “American Indian Achievement Gap” or when referring to the racially identified data element (see data limitations). *Indigenous* and *Native* are used in attempt to recognize the many Indigenous groups and tribes in Montana— including but not limited to the Crow, Northern Cheyenne, Sioux, Gros Ventre, Assiniboine, Chippewa, Cree, Blackfeet, Salish, Kootenai, Pend d'Oreille, and Little Shell Chippewa— each intrinsically linked to identity. These listed tribes capture those most often

represented in Montana; however, it is important to acknowledge that Native students in Montana are not limited to these tribes, and students from tribes not listed here or from outside Montana may also be present.

### Assumptions, Limitations, Delimitations

Functioning from the platform of CRT, and more specifically from the Theory's branch of QuantCrit, this study functions under the assumption that race eclipses other forms of exclusion. Individuals do not have just one form of identity that is placed on them, and there is not a singular experience for an entire group of people that every member experiences as the same. A shared history may exist, but this does not elicit or assume one shared experience. This anti-essentialist perspective informs the quantitative intersectionality approach where race is foremost recognized as a social location informing student experience. In addition, gender and poverty are also critical social locations for informing student experience. Amidst the extensive social location combinations generated for the analysis of this study, there is not a singular experience across, within, or between the bounds of these various 28 social locations.

Significant limitations exist for the way data is collected for a couple of the elements. The data available to characterize and recognize race is one such example. There are five federally recognized categories for coding data on race including 1) American Indian or Alaska Native, 2) Asian, 3) Black or African American, 4) Native Hawaiian or Other Pacific Islander, and 5) White. In addition, there are two categories for data on ethnicity including 1) Hispanic or Latino and 2) not Hispanic or Latino (DOI, 2021). Yet, racial identity is fluid and one part of many intersections defining identity. Social construction thesis acknowledges that race is the product of social thought, "not objective, inherent, or fixed, [corresponding] to no biological or genetic

reality” (Delgado & Stefancic, 2017, p. 8). *Federal race/ethnicity* as the five categories of race are used in this study when referring to race as the data element. *Racial identity* is utilized when considering its socially constructed quality. One area that requires specific articulation for clarity is when referencing Montana Indigenous Peoples. Federal race/ethnicity as a data element generalizes all tribal affiliations into a collective group referred to as *American Indians*. In this way, such specificity in specific tribal recognition is lost. This study utilizes *American Indians* when referring to the data element, and *Indigenous* or *Native* when attempting to acknowledge the complex identities of individuals within a collective community of Montana’s First Peoples. All three terms are limited in acknowledging the complex community and individual identities represented in these conglomerate and collective student groupings.

Another significant data limitation exists in how student class or poverty is measured. Understanding the ways poverty impacts students’ academic experiences is critical for social science research dedicated to informing equitable policy and practice decision-making. However, measuring student poverty has historically faced limitations where researchers are forced to default to measures of students’ eligibility for free and reduced-price lunch (FRPL) in participation with the National School Lunch Program as a proxy measure for student poverty. FRPL participation data was not designed for education research and policymaking (NCES, 2021a), as the data places students’ poverty into one of three categorical levels: receiving free school lunch (“high-level poverty”), receiving reduced-price lunch (“mid-level poverty”), and not eligible for FRPL (“low-level poverty”). Further, few students have their household incomes verified to confirm eligibility (NCES 2021b) disrupting the validity of the student-level indicator. In addition, using FRPL as a proxy measure for student poverty is limited as an accurate

indicator due to school-level participation. Various schools, such as Title I schools, provide free or reduced meals to all their students regardless of individual student-level poverty (NCES, 2021b). In such cases, FRPL data function more as a school-level poverty indicator rather than a student-level poverty indicator. While utilization of the SIDE metric for Montana schools provides an improved, continuous measure for school-level poverty, these measures at the student-level are currently unavailable due to access and data quality concerns of student addresses in Montana. In this way, FRPL data remain the option available for considering student-level poverty, however limiting the element is on data validity.

Across all data elements used, recognition of relational findings rather than causal is an important acknowledged limitation of any statistical analysis—perhaps an understanding often neglected in “achievement gap” literature more generally across policy and practice. The relationship between achievement and graduation is relational, where certain student groups achieve at lower rates and dropout at higher rates. However, causation cannot be assumed. Similarly, the investigation of the relational impact between students’ social locations, school-level poverty, and student mobility will help provide better understanding of the social and experiential factors impacting student achievement in Montana, but causation cannot be assumed.

While better understanding students’ social locations, impact of poverty, and impact of mobility on their academic experience throughout the K-12 environment is essential to grapple with defining, analyzing, and responding to “achievement gaps,” one delimitation of this study is to set boundaries around investigating only high school students. The “achievement gap” between Native and non-Native students in Montana is acknowledged for elementary, middle

and high school students, where achievement is measured using both standardized test scores and graduation rates (OPI, 2022; 2020a; 2018). This study focuses on only high school students where achievement is measured using ACT composite scores and completion is measured using end status (graduation/dropout) indicators. Another delimitation of this study is the longitudinal scope of student data considered. While generational, cyclical, and persisting educational inequality is evident between Montana students, this study sets boundaries around school years (2018 and 2019) in alignment with the recently created SIDE measures (2019) for Montana high schools which are in-part based on recent American Community Survey (ACS) data (NCES, 2021b).

As a quantitative designed study, boundaries are set around examining qualities of students' academic experience through set measures rather than aligning to experiential or narrative data. In this way, the Montana "achievement gap" is redefined through data-informed means in this study, but unaccompanied by the stories and perspectives of students and stakeholders. While quantitative work exists investigating educational inequalities based on students' characteristics- such as gender, race, class- application of intersectionality to acknowledge the complex quantitative impact of such characteristics is only emerging (McMaster & Cook, 2019). This study sets boundaries around a quantitative approach to investigating the impact of intersecting social locations, school-level poverty, and student mobility on academic success as part of this emerging field while acknowledging a continuing need for future work to align qualitative data for the most comprehensive understanding of redefining Montana "achievement gaps."

It is important to consider the reliability of some variables' consistency in measurement over time. Pre-COVID data (2015–2019) was intentionally used for this study to avoid the significant disruptions the COVID-19 pandemic had on educational data, including student mobility patterns. The pandemic drastically altered students' movement between homes, neighborhoods, and schools, and these changes could impact the consistency of mobility data if collected during or after the pandemic. Additionally, the results of this study do not capture the effects of COVID-19 on outcome measures, and it is possible that any re-bounding effects post-COVID could differ significantly from the pre-pandemic trends observed here. Future studies should consider the pandemic's impact when interpreting findings from more recent data.

### Chapter Summary

The current Montana “achievement gap” focuses on highlighting student academic achievement and completion differences between Native and non-Native students, and in this way expects only to find a race gap to explain such differences. Through QuantCrit and quantitative intersectionality projects that unveil race–gender-class gaps for Montana students, the goal becomes to reveal the inequalities that conventionally remain invisible for students. The Montana “achievement gap” also insufficiently considers the impact of various student experience factors impacting access to academic achievement and completion, such as student mobility. By layering understanding of students' mobility impact with their social context (student social locations and school poverty), a more thorough data story may ensue for the Montana “achievement gap” ultimately informing the decision-making processes to support our students.

## CHAPTER TWO

## LITERATURE REVIEW

Commonly referred to as “achievement gaps,” or the “difference in academic outcomes between historically advantaged and disadvantaged groups” (Valant & Newark, 2016, p. 331), trends of lower academic success among racial groups are a major practice, policy and research concern (Carey, 2014; Shukla et al., 2021). Since the Coleman Report (1966), a range of stakeholders have tried to address the achievement gap through funding, reform initiatives, research, policies, and educational practices. These efforts centralize on the mission of eliminating disparity between students’ academic outcomes (Valant & Newark, 2016). As decades of work and policy have shaped the discourse and understanding of what is meant by “achievement gaps,” one implication is that of racialized “achievement gaps” or the observed gap in academic performance between White and Asian students, and students of color (Noguera, & Wing, 2006). Educational environments across the nation navigate racism and marginalization as a permanent, social construction accepted with normalcy, as evident in tangible structural inequalities such as racialized academic “achievement gaps.” This chapter examines “achievement gaps” through critical frameworks to consider how disproportionate outcomes are driven by racism rather than by race. In particular, this chapter articulates the frames of inequity of space and inequity of resource around opportunity factors impacting success. Inequity of space aligns the histories of land and school reform for Indigenous people to the ways schools reveal how power is structurally inscribed and reinforced. Inequity of resource weaves the abundance of experiential factors impacting educational inequity and academic success, namely poverty and mobility within the confines of this paper.

### Achievement Gaps in Educational Discourse

The gap in academic achievement between students of color and white students cannot be summed by performance scores alone. Rather, the perception is left unacknowledged by the abundance of inequalities which impact student performance and the disparity between students (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010). Various inequalities impacting these gaps include “the teacher quality gap, the teacher training gap, the challenging curriculum gap, the school funding gap, the digital divide gap, the wealth and income gap, the employment opportunity gap, the affordable housing gap, the health care gap, the nutrition gap, the school integration gap, and the quality childcare gap” (Milner, 2010, p. 9). Educational inequity is observed in the continuation of students from the most privileged backgrounds continuing to dominate educational opportunities, and is a significant enduring social problem that continues to be examined extensively in social science research (McMaster & Cook, 2019). While students of color, especially those students from low socio-economic backgrounds, experience proportionally higher dropout rates and lower academic achievement (Valencia, 2002) the gap—or what is perceived as deficit—is a complex reality of factors, opportunities, and experiences.

While equity in education has been a focus in policy and research since the 1960s, the term “achievement gap” has only been more widely accepted in the last two decades and functions as a term that exacerbates the observed disparities. The Coleman Report (1966) uses “test score gap” terminology when referring to the disparity of outcome measures between groups of students. With the major education reform in 2002 under the Bush administration of No Child Left Behind (NCLB) and the requirements of reporting academic achievement data by race (Warikoo & Carter, 2009), the term “achievement gap” became the norm. However, this

term insinuates student deficit, where in particular the problem of achievement is perceived as the deficit of students of color (Chambers, 2009). In response, historic responses to various adopted “achievement gaps” insinuates the problem resides with groups of students, and more specifically, students of color. In turn, this avoids placing responsibility on the structure itself challenging the common deficit model (Chambers, 2009). In the State of Montana, the commonly accepted “achievement gap” refers to the differences in academic outcomes between Native students and their non-Native peers.

As part of the movement of NCLB (2002) to collect and report on the academic outcomes of students and schools, the nation has participated in decades of generating “achievement gap” data and reports. In Montana, the *American Indian Student Achievement Report*— often referred to as the “Achievement Gap Report”— has been generated on a biennial basis. Allowing the use of this adopted term insinuates student deficit thinking, particularly of Native students, and displaces the responsibility away from the systems (i.e., federal and state education systems, school systems, etc.). Furthermore, this report functions as a racialized “achievement gap” (Noguera, & Wing, 2006) comparing academic outcomes between Native and non-Native students. The report summarizes the success of Native students using performance scores alone (OPI, 2018; 2020a; 2022) and ineffectively illuminates the complex and various inequalities which inform disparity in performance scores. The purpose of collecting, analyzing, and reporting data is to convey a story of racial inequality that can be acted upon. Yet, the story behind data is often complex and involves the intersections of factors that impact individuals’ experiences (SLDS, 2023). In this way, a redefining of “achievement gap” discourse must ensue. Not only should the Montana Office of Public Instruction (OPI) adapt terminology back to its

original form of *American Indian Student Achievement* by removing “achievement gap” language across reporting, policy and conversation, but the story of Native student success in Montana may be more accurately represented by involving intersections of demographic and experience factors.

If the data story of Native students in Montana adopted data exploration of various opportunity factors, or those factors which illuminate the inequity impacting achievement outcomes, in addition to performance metrics, we might take a step in the direction of placing the person back in the data point. Various inequities impacting the disparity in achievement outcomes include access to quality educators, provision of quality teacher training, access to quality and relevant curriculum, adequate provision provided through school funding, access to technology and internet, consideration for disparity in wealth and family income, access to employment opportunities, access to quality and affordable housing, access to quality and affordable healthcare, nutrition, and childcare (Milner, 2010) to consider a few. The emphasis on structural inequality is important as it reframes the deficit narrative surrounding individuals and groups of individuals by emphasizing the inequality of social structures. Thus, reframing the “achievement gap” as an “opportunity gap” more accurately conveys that the disadvantages lie within educational structures and not the individual. If OPI desired to adopt “opportunity gap” terminology as part of the reporting effort of access and success of Native students in Montana, it would need to also adopt the analysis and reporting— and in some scenarios the collection of— these factors of inequity. Some of these areas of inequity OPI currently has access to collected data, in which case redefining academic achievement through these measures is simply an effort of inclusion in the reporting. Challenge will form around those areas of inequity OPI does not

currently have sufficient access to data. One example of such a factor impacting inequitable access is student mobility, or the movement of students between schools. Utilizing mobility, in alignment with spatially informed opportunity factors such as school-level poverty, as well as demographic factors illuminating intersectionality such as gender, race, and class, is an effort to expand the data story for Native students' academic success in Montana. Understanding inequitable access in U.S. schools must embrace adaptations rather than stagnation by merely replicating efforts of the foundational Coleman Report (1966) and disaggregating understanding by groups.

#### Policy Surrounding “Achievement Gap” Discourse

The collection, analysis and reporting of “achievement gaps” in policy, research and literature is not a recent addition to educational discourse. While implementation of collecting and reporting to racialized “achievement gaps” can be traced to policy and efforts surrounding No Child Left Behind and the Bush administration, its foundations date back decades before. Federal interest in understanding patterns of academic achievement and economic success by race, as well as “gap” language, presents in the U.S. as early as the 1960s.

The Moynihan Report (1965). Under the Johnson presidency, the Assistant Secretary of Labor released a report on Black poverty in the U.S. attempting to establish statistical significance around the relationship between economic and social conditions. More specifically, the Moynihan Report concluded the high rate of families led by single mothers served as an obstacle to Black economic and political equality (Moynihan, 1965). Strong criticism followed the publication, and the report remains controversial today with responses akin to “blaming the victim” (Ryan, 1976; Skrentny, 2008). Poignant to the emergence of “achievement gap”

language in the educational field, the Moynihan Report leveraged some of the first “gap” language among outcomes disaggregated by race. In regards to economic welfare, Moynihan claimed the “gap” between Black families and other groups was widening, and concluded that the structure of family life in Black communities required access to jobs so Black men would not become detached from their roles as husbands and fathers. Following the Moynihan Report, the Coleman Report seemed conservative in its implications of families’ role in educational inequality (Downey & Condrón, 2016).

The Coleman Report (1966). Again, under the Johnson presidency, the U.S. formally began dialogue of equitable education in the nation’s public school system. A decade after efforts to desegregate schools through the Supreme Court decision in *Brown vs. Board of Education* (1954), the nation was concerned with shortcomings in opportunities provided by schools for the achievement of its students. In July 1964, James Coleman was tasked by section 402 of the Civil Rights Act (42 U.S.C. 2000c-1) to tackle a large social science survey within a timeframe of only two years. The survey and report, referred to as the Coleman Report (1966), produced a two-fold objective: first, it provided description of the nation’s educational system and second, it analyzed how the state of the nation’s educational system related to academic achievement (Cain & Watts, 1970). The Coleman Report served as a catalyst for discussing gaps in performance between Black and white students, revealing what many anticipated: segregation still existed in public schools. However, the report also revealed that beyond amenities and funding, there were complex socioeconomic factors impacting students’ ability to learn (Chambers, 2009).

While the Coleman Report does not coin the term “achievement gap” its findings of disparity between the achievement of Black and white students introduced a way of thinking

about the success of schools. Following the report, concerns were discussed using the term test score gap. The Coleman Report began discussion of gaps in performance between student subgroups, often disaggregated by race (Chambers, 2009), though it did not offer any recommendations based on its findings for policies or programs of the federal, state, or local government agencies. Rather the U.S. Commissioner of Education, Harold Howe [1966-1968], encouraged the report be utilized by the U.S. Office of Education to examine and respond to the educational opportunities of all students across the nation in decision making (p. iv). The report served as the first comprehensive collection of data across the U.S. on student and school success through four major questions: (1) the extent to which racial and ethnic groups are segregated in public schools, (2) whether schools offer equal educational opportunities in terms of educational quality, (3) the amount of student learning as measured by standardized achievement tests, and (4) what relationships exist between students' academic achievement and the schools they attend (Coleman et al., 1966).

The overarching findings of the Coleman Report concluded that the variation in students' academic success shared a strong relationship to family environment and very little relationship to school environment or school-level factors such as per-pupil expenditure. Furthermore, that family environment serves as a primary influence not only on academic success, but the success of the student later in life as well (p. 325):

One implication stands out above all: That schools bring little influence to bear on a child's achievement that is independent of his background and general social context; and that this very lack of independent effect means that the inequalities imposed on children by their home, neighborhood, and peer environment are carried along to become the inequalities with which they confront adult life at the end of school.

In addition to the importance of a child's family background on performance, the report concluded the social and economic composition of the student body also served as a predominant influence on achievement. Particularly for a working-class child, students in integrated socioeconomic environments performed better. The survey results of the Coleman Report illuminated test score disparities among disaggregated groups, leading to later development of "achievement gap" discourse. Results found that even when resources were relatively equal within regions, educational outcomes were not, as Black students were testing several grades below their white peers in math and reading (Coleman et al., 1966). The Coleman Report reframed how educational inequality was explained by using test score disparity and indicators outside of school and teacher quality.

Coleman and team (1966) and later Jencks' (1972), research on educational inequality should not be misinterpreted as arguing that the school and indicators of school and teacher quality do not matter in understanding disparity, but rather Coleman and Jencks challenge that schools play only a minor role in describing "achievement gaps" (Downey & Condrón, 2016). Accepting only a minor role of schools and the system unearthed a deficit model emphasis on the student and the student's environment on achievement. This deficit lens (Jencks & Phillips, 1998; Ladson-Billings, 2006) on "achievement gaps" remains a core focus of education research and policy today—over fifty years later. Understanding resource segregation in public education as a system of inequitable access geographically defined by school districts (Douglas, 2021) has been largely ignored in policy to understand how schools influence inequality. The Coleman Report did not offer any recommendations based on its findings for policies or programs of the federal, state, or local government agencies, a mantra that seems to be continually acceptable.

Rather than emphasizing inequitable educational opportunity amidst the systems, policy has largely focused on individual-level patterns of achievement (i.e. disaggregating achievement by race) without offering tangible ways of responding to individual-level disparity.

Statistical Policy Directive 15 (1977 & 1997). A point and case of policy focusing on such individual-level patterns is Statistical Policy Directive No. 15 (SPD 15) guiding how race is defined in policy, data collection, and data reporting. Not only were pivotal points such as the Coleman Report aligned to revealing disparities— often provided as disparities based on race disaggregation— in the nation’s schools, but the reporting mechanisms for classifying race contributed to defining “achievement gaps” as racialized, and as a fault of the individual student rather than the system. SPD 15 has served as a quiet backbone to how racialized “achievement gap” data has been collected and reported over two decades of Elementary and Secondary Education Act reform of both No Child Left Behind and Every Student Succeeds Act.

From the civil rights laws, SPD 15 was initially developed in 1977 by the Office of Management and Budget (OMB) with the intention of providing consistent data on race. The goals were twofold: (1) to provide the comparability of race across datasets and (2) to ensure quality in the procedures for collecting race data (The White House, 2023). As discourse surrounding equitable access and “achievement gaps” developed after the Coleman Report, SPD 15 provided a uniform approach for research and data collection that examined by racial groups. Additionally, as policy formed, schools were expected to report various data— such as race/ethnicity— where SPD 15 guided their methods.

SPD 15 was revised once resulting in the 1997 *Standards for Maintaining, Collecting, and Presenting Federal Data on Race and Ethnicity* which function as the current standards still

adopted today (Initial Proposals for Updating SPD 15, 2023). These current standards require two separate race and ethnicity questions and five race categories including White, Black or African American, American Indian or Alaska Native, Asian, and Native Hawaiian or Other Pacific Islander (DOI, 2021). As a pivotal guiding standard, SPD 15 has been fundamental for how racialized “achievement gaps” are collected, reported, and interpreted. For example, examination at the state or federal level of minoritized groups often reports by students who identified as White and Asian to students who identify as the remaining categories.

Decades later, SPD 15 is currently under process for revision. As of January 26, 2023, the initial proposal was open for public comment (The White House, 2023). It is recognized that the federal statistical standards should adapt to evolving needs and uses of data: “Federal race and ethnicity standards are inherently complex because they seek to capture dynamic and fluid sociopolitical constructs” (Initial Proposals for Updating SPD 15, 2023, p. 5377). Revision efforts seek to collect more granular data to understand within-group disparities better. For example, disaggregated data for the Asian population may provide identification of Japanese, Hmong, and Cambodian. Revision also intends to provide more categories of identification including a category for Middle Eastern or North African (MENA) as well as Multiracial/Ethnic.

The working group for the revision of SPD 15 has adopted twelve governing principles to guide their review. In summary, these principals recognize that the race and ethnicity categories are sociopolitical constructs and are not an attempt to define race and ethnicity biologically or genetically. Rather, self-identification with access to clear and generally understood terminology facilitates respect for individuals. In addition, that categories should be comprehensive with useful data aggregations for practical data analysis across federal datasets. In this way, while

additional categories are encouraged, they can be aggregated recognizing state, local, and Native governments data needs. Agencies are encouraged to collect and provide more granular data than the minimum categories for race and ethnicity. Lastly, that changes made to 1997 standards should be based on sound research and collaboration, provide adequate time between category adoptions so historical data series can be statistically adjusted, and adhere to public law (Initial Proposals for Updating SPD 15, 2023). While such revisions to the standards would not address the need to examine academic disparity and inequity with factors outside of racial constructs, it would function as a progressive step in responding to the current standards' limitations. Regardless, SPD 15 was born from the Coleman Report's racial disaggregation and individual-level patterns of achievement focus, has been further utilized by educational reform over the last two decades, and is guided by very little system-level accountability and response.

Nation at Risk (1983). While education was not centerstage in the 1980 presidential election (Pomper, 1981), the creation of the National Commission on Excellence in Education (NCEE) in 1981, an eighteen member panel, effectively produced an influential report which brought educational issues back to the attention of the federal government. *Nation at Risk*, in addition to other reports released in the early 1980s, played a significant role in the movement of education reform focused on graduation requirements and competency tests. By the mid-1980s, policymakers were largely disappointed by incremental change and the continued presence of disparity between advantaged and disadvantaged students (Vinovskis, 2009). A *Nation at Risk*, published in 1983, contributed to the perception that American education was declining (Ravitch, 2003). Some argued the report was misleading and too pessimistic regarding student

achievement (Stedman & Smith, 1983) and that the NCEE utilized a rhetorical strategy that exaggerated the data detailing to story of decline (Vinovskis, 2009).

In 1984, Secretary of Education Terrel Bell instituted the “wall chart,” a ranking of states by their state-level student achievement data based on ACT and SAT scores. During the 1980s, state governors began to acknowledge the need for more reliable state-level assessment data outside of just the ACT and the SAT exams. In 1986, under the lead of Secretary of Education William Bennett, the National Assessment of Educational Progress (NAEP) became the avenue for state-level data. By the 1990s, the NAEP significantly contributed to the movement of collecting and disseminating state-level data on student achievement (Vinovskis, 2009). The election of President Bush, however, turned brought educational issues centerstage as part of his election, once again evolving the way achievement data was collected, analyzed and utilized.

No Child Left Behind (2002). The Elementary and Secondary Education Act (ESAE) as a federal education law, dating back to President Johnson and administration, has seen continued adaptation and renewal. One major adaptation to ESAE was under the Bush administration through No Child Left Behind (NCLB). While NCLB continued “previous patterns of federal educational provision and funding” (Urban & Wagoner, 2014, p. 351), what made this adaptation significant was the integration of utilizing “standardized testing as the vehicle by which public schools would be measured” (p. 351). This mandated testing in all public schools, effectively placing priority on schools’ achievement and longitudinal measurement of that achievement in hopes to inspire growth. Further, NCLB was the first federal legislation for education that required schools to report on academic achievement data where the data was disaggregated by

race (Warikoo & Carter, 2009). At the federal level, data began to emphasize gaps in achievement between student groups, particularly for minority students and students of poverty.

NCLB is one of the largest educational reforms since the 1960s (McGuinn, 2006) and a significant contributor to the birth and use of the racialized term “achievement gap” (Chambers, 2009). The racial “achievement gap” can be defined as the observed gap in academic performance between two student groups, where white and Asian students make up one and students of color the other (Noguera & Wing, 2006). While current policy still functions as a product of racialized “achievement gaps,” significant critique is that the gap in academic achievement cannot be summed by performance scores alone. Rather, the perception of the gap is left unacknowledged by the abundance of inequalities which impact student performance and the disparity between students (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010).

This education reform placed priority on the measurement of student achievement to address inequity across the nation’s schools, but gaps were not significantly closed nearly a decade later. Through examining longitudinal trends in NAEP scores, the “achievement gap” has been effectively stagnant: “[A]s a nation, we are no closer to closing the achievement gap today than we were two decades ago” (Boykin & Noguera, 2011, p. 12). The critical question that remains is whether the “achievement gap” can be narrowed without addressing system-level inequities impacting academic access and achievement such as health, housing, and income (Boykin & Noguera, 2011). The improvement of students who have not done well in school historically became a primary focus through the law and policies set in place through NCLB. NCLB intentionally exposed “achievement gaps” between historically underserved students and their peers continuing dialogue on educational quality in U.S. schools (ESSA, 2023). While not

without its challenges, NCLB turned educational reform toward school accountability, seen through the state level as strict federal mandates (OPI, 2018; 2022).

NCLB upheld school accountability by scaling up the federal role which grew out of a concern the U.S. educational system was no longer internationally competitive. Fairly uniform contention developed from educators and school leaders for the strict federal role of NCLB as states and schools were held responsible for demonstrating the progress of students, especially minority student sub-groups such as ELs, students of poverty, special education students, and students of Color. Racialized and disaggregated data reporting on student groups became a daunting task for schools knowing if they did not comply, they were subject to lose their Title 1 funds. NCLB is the epitome of reform functioning from a student deficit lens as both the reporting expectations, progress outcomes, and incentive plan ignores the paramount role of institutionalized systemic inequality students navigate, especially minority student groups such as ELs, students of poverty, and students of color.

Every Student Succeeds Act (2015). December 10th, 2015, the Obama administration reauthorized ESEA as Every Student Succeeds Act (ESSA) with major revisions from NCLB, yet the same intention of upholding school accountability prevailed. One of the key goals of ESSA as defined by the U.S. Department of Education (USED) articulates this central thread: “The law... [m]aintains an expectation that there will be accountability and action to effect positive change in our lowest-performing schools” (ESSA, 2023) where low performing schools are those where sub-groups of students consistently underperform compared to their peers in both academic performance and completion. One major product of school accountability under ESSA is the execution of state and local report cards which communicate district educational spending,

student achievement on standardized assessments, graduation rates, teacher qualifications, school environment measures, as well as an overview of each state's accountability system. At the local level, each state articulates the indicators by which the state measures schools' success. In addition, the states provide which schools have been identified for improvement and support based on their performance. These designations include universal, targeted, and comprehensive support.

The accountability provisions of ESSA require states to provide comprehensive support and assistance to no less than 5 percent of the lowest performing schools receiving Title 1 funds and any public high school with less than a 66.9 percent graduation rate (Sec. 1111[c][4][D]). Regarding assessment accountability, no less than 95 percent of students must participate in a state's standardized assessment or alternate assessment, and 95 percent of all students within each group (Sec. 1111[c][4][E]). In this way, statewide assessments are required for the subjects of math and English language arts for all students grades 3 through 8 and at least once in both subjects grades 9 through 12 (Sec. 1111[b][2][B][v][I]). Statewide assessments are required for the subject of science at least once during grades 3 through 5 and at least once during grades 10 through 12 (Sec. 1111 [b][2][B][v][II]). Another important aspect of ESSA's assessment requirements handles students identified as English Learners (ELs). It mandates assessment of ELs after a student has been in the U.S. for one year. For the first year, EL test scores do not contribute to a school's rating. The second year EL test scores must be incorporated using a growth metric. However, by the third year, EL test scores are included just as any other student's score in the overall school rating (Sec. 1111[b][2][G][3][A]).

Montana's Consolidated State Plan under the Every Student Succeeds Act (OPI, 2018; 2022) and accountability system has been led under the leadership of State Superintendent Elsie Arntzen where she has emphasized local control. Montana students take the Smarter Balanced Assessment (SBAC) in grades 3 through 8 for both math and English language arts, the Montana Science Assessment (MSA) in grades 5 and 8 for science, and the ACT in grade 11 for math, English language arts, and science, fulfilling the standardized assessment data collection requirements of ESSA. In addition, alternate assessments are offered to Montana students with Significant Cognitive Disabilities. Regarding assessment of EL, the Home Language Survey reveals German (0.34 percent), Spanish (0.21 percent), and Native Indigenous languages (less than 1 percent) are spoken across Montana homes, however in total, less than 1 percent of students speak one of these as their primary language in the home. The OPI defines 10 percent or more of students with a primary language other than English as significant for providing the assessment in alternate languages. Therefore, the OPI only provides the Spanish version of the SBAC in mathematics to students. For those students with a Native Indigenous language as the primary home language, the OPI has determined the English version of statewide assessments provides the most effective way for students to demonstrate their understanding (OPI, 2018; 2022). It should be noted that of EL students who identify as American Indian or Alaskan Native or multi-racial in Montana, hardly 1 percent have been English proficient since the release of Montana's Consolidated State Plan in 2018 (GEMS, 2023a).

While ESSA made monumental shifts away from the strict federal mandates of NCLB, racialized achievement reporting persists and state report cards in Montana only emphasize the disparity between Native students and their non-Native peers. While ESSA released NCLB's

strict federal mandates to local state control, the disparity between students has been largely unchanged over the last two decades and underperforming schools continue to require support. In Montana, schools designated as Comprehensive are predominantly schools on reservation land and of majority Native student population. Since the adoption of Montana’s Consolidated State Plan, sixty-three schools have been designated as Comprehensive. Of these schools, almost 80 percent are located on reservation. An additional approximate 15 percent, while off reservation, have a Native student population greater than 10 percent. This means the great majority of schools identified as Comprehensive under ESSA are predominantly Native schools, and further, that the majority of schools in the bottom 5 percent and with graduation rates lower than 66.9 percent are predominantly Native schools (OPI, 2023b).

### Theoretical Precursors to Discussing “Achievement Gap” Discourse

Founding efforts, such as the Coleman Report, to better understand the academic achievement of students in U.S. classrooms— especially of racialized differences in achievement— did not utilize “achievement gap” language and terminology. Common use of “achievement gap” discourse became dominant with NCLB policy. In this way, racialized “achievement gaps” function as a more recent phenomenon— approximately 20 years— in the literature and in policy. Not only is “achievement gap” discourse and policy a relatively recent outcome of educational reform, but it functions from a student deficit perspective focused on racialized discrepancies making it inherently racist. The perception of racialized “achievement gaps” in U.S. schools is often left unacknowledged by the abundance of inequalities which impact student performance and the disparity between students. In this way, the theoretical precursors of “achievement gap” discourse are a foundation built on sand.

The current American education system navigates one of the greatest challenges for educators and policymakers by facing the improvement of academic access and success for economically disadvantaged and racial/ethnic minority students as millions attend schools that are segregated, inequitably financed, and ill-equipped in curricula (Valencia, Menchaca & Valenzuela, 1993; Valencia, 1997). The conventional means of measuring academic performance illustrates “achievement gaps” for economically disadvantaged and racial/ethnic minority students shaped by systems and histories of normalizing deficit thinking. Historical acceptance of racialized deficit thinking established an assumption of biological and cultural deficiency as foundational roots leading to segregated classrooms and implicit bias in recent history. While cultural deficit theories replaced genetic deficit theories, the foundation of thought placed responsibility on the student and remained culturally biased. Theories of communication process emphasize students’ communication and culture as catalyzing the student’s perceived motivation and ability as their language and lifestyle were seen as culturally deprived. Caste theory, a model by Ogbu, illuminates a case where involuntary minorities living in a racist society, perceive their academic opportunities with limitations, in turn, this student perception develops a belief of academic limitation. And, structural inequality models examine cultural conflicts between culture, home, and school considering the forces of historical, political, economic and social relationships.

### Building Out of a Student Deficit Model

Student deficit discourse is contagious in a few corners of theory. The deficit thinking model is an inherently racist discourse (Menchaca, 1997) assuming deficit exists due to a student’s own deficiencies such as intellectual ability, lack of motivation, or immoral behavior

(Valencia, 2010). Trends— such as racial disparity observed in “achievement gaps”— supposedly illuminates alleged deficit caused by genetics, culture and class, and familial socialization. A framework of student deficit absorbs obvious problematic assumptions. Within the context of understanding “achievement gaps,” it assumes disparity in achievement is due to the child’s lack of ability or motivation. The deficit thinking model has strong foot hold in historical theory focused on internal deficits or deficiencies such as intellectual ability, linguistic shortcoming, lack of motivation and genetics with a failure to consider external attributions of school failure (Valencia, 1997).

In 1971, William Ryan published *Blaming the Victim* attacking the very backbone of deficit thinking as a reaction to reform and the policies of the 1960s: “[W]e have programs of ‘compensatory education’ to build up the skills and attitudes of the ghetto child, rather than structural changes in the schools” (1971, p. 8). Following the history of deficit thinking in education, state constitutional statutes, state educational agency policies, judicial outcomes, state legislation, local school board policies, and classroom teacher practices are fueled by class and racial prejudice. So far as to even argue deficit thinking is in itself a form of oppression (Valencia, 1997). However, the roots of deficit thinking extend well before the educational reform and policies of the 1960’s. Rather, the student deficit model traces its influences to ideological and economic concepts establishing racial inferiority and dominance in colonial America. These influences spread like disease throughout domains of American society, including education and schooling of the child.

Roots of Deficit Thinking. Socially accepted American deficit thinking arguably traces back to the settlement of America in 1620 with the Pilgrims. Perhaps not that the Pilgrims were

an intentionally racist people, but rather they brought with them early seventeenth century racial beliefs when they encountered Indigenous peoples. In addition, British law refused to recognize Indigenous peoples as legal land owners, rather, these first European settlers were granted concepts of ownership through farming plots and lands to settle their families. Furthermore, the religious incentive of the Pilgrims cascaded generations of rationalizing they were 'God's Chosen People' (Feagin, 1989; Menchaca, 1995; Menchaca, 1997) and superior race with a destiny to govern America (Menchaca, 1997).

Early colonization of America continued with the intensive interest from the British Crown on expanding real estate in America. British military spread the wings of its conquest attacking and relocating Indigenous peoples (Wolf, 1982), and after massacres of Indigenous populations, the practice of importing slaves commenced (Menchaca, 1997): "Thus the enslavement and exportation of Africans to the American-British colonies was an expedient response to the labor demands generated by Anglo-Saxon usurpation of Indian lands" (Menchaca, 1997, p. 16). Deficit thinking toward Indigenous peoples and Africans was racial belief justified by the colonial government removing the concept of their human-ness, condoning slavery, and even positioning it as God's will (Lyons, 1975; Menchaca, 1997; Weinberg, 1977). In this way, the inferiority of people of color through themes of biological inferiority (Nott & Gliddon, 1854, 1857) and cultural deprivation designed the evolution of deficit thinking in America on the assumption that people of color are biologically or culturally inferior to white people. Bleeding into American education, racist beliefs and economic interests were deeply intertwined even so much as racial minorities were prohibited from public education. Even once students of color were given the opportunity of an education, it was far from equitable in

segregated and inferior classrooms (Menchaca, 1997). The deficit thinking which segregated American classrooms is rooted in the same deficit thinking that normalized Indigenous massacres and slavery.

Cultural Deficit Theories. In the 1950's anthropologist Oscar Lewis (1960) began formulating an idea known as "culture of poverty," or that among generations of lived poverty traits such as helplessness, feelings of inferiority, and lack of trust in social institutions cyclically repeat themselves to create a culture of poverty (Huffman, 2010). Lewis's hypothesis developed into what became known as cultural deprivation theory or cultural deficit theory. Cultural deprivation theory is the argument that the lack of academic achievement common among people living in generational poverty was because of a lack in the home environment, instead remaining focused to survival mentalities and immediate needs (Bloom et al., 1965; Huffman, 2010). This theory removed the weight of responsibility from the schools (Gans, 1995) and was later criticized. As a response, cultural discontinuity theory emerged. Cultural discontinuity theory identifies the lack of academic achievement, especially for minority students, is due to factors rooted in the school rather than cultural deficiency of the homes, particularly the communication in the dynamic cross-cultural nature of the classroom (Huffman, 2010). Some researchers have designed approaches to quantitatively investigate cultural discontinuity, but issues have been raised regarding the limited empirical research that exists (Valencia, 2010).

Communication Process Theories. Theories of communication process emphasize the role of culturally learned verbal and nonverbal communication styles in explaining academic success and failure. Specifically, it is the cultural differences in speaking and listening between the student's speech network and norms to the teacher's speech network and norms that causes

miscommunication (Erickson, 1987). Further, it is the miscommunication in the classroom, as well as the power difference between teacher and student, responsible for a diagnosis of student deficiency (Mehan, 1978; 1980; 1987). This position provided “a way of seeing classroom troubles as inadvertent misunderstanding— teachers and students playing into each other's cultural blind spots” (Erickson, 1987, p. 336). In the 1970s, Ogbu criticized the position and instead presented that the cause of inequity was outside of the school.

Caste Theory. Ogbu’s cultural-ecological theory considers why some minority groups do well in school while other minority groups are restricted from their academic success. “The cultural-ecological theory of minority schooling takes into account the historical, economic, social, cultural and language or dialect situations of minority groups in the larger society in which they exist” (Ogbu, 2003, p. 45) through three major social forces: political, economic, and cultural. In this way, Ogbu identified three types of American minorities: *autonomous minorities* (minority status but are not subject to historic subordinate position such as the Amish), *voluntary minorities* (groups who migrate to the U.S. to escape political and economic circumstances, but historically have done well academically such as the Chinese and Japanese), and *involuntary minorities* (people who were forced through slavery, conquest, or colonization, people who have the least social, political and economic power, including Blacks and Natives) (Huffman, 2010). Involuntary minorities, also referred to as ‘Native minorities’ by Warikoo and Carter (2009), are historically people who have less access and success in the academic arena. Ogbu’s framework has been critiqued for being endogenously based where minority students may develop a self-belief of school failure (Valencia, 2010).

Structural Inequality Theory. Structural inequality theory is similar to cultural discontinuity theory in that it attempts to explain how educational outcomes are influenced by cultural conflicts though much more focused on the “social structural phenomena” within the institution of education (Huffman, 2010, p. 63). In this way, the focus turns to poverty, as well as personal and institutional racial discrimination, and how the society’s structure impacts educational success. In turn, structural inequality theory looks beyond the cultural conflicts between culture, home, and school considering the forces of historical, political, economic and social relationships and their impending influence (Huffman 2010). When considering the disparity in academic achievement for students, inequitable access must be considered across cultural, economic, and political contexts– all of which susceptible to systemic inequities observed in the role of history: “The systems that have emerged are the consequences of historical influences modified by current political pressures...[and establish] the basis for inclusion and exclusion in various societal institutions” (Pearl, 2002, p. 336). For example, structural inequality theory would recognize Native students in Montana have educational outcomes impacted by histories of colonization and assimilation, geographies of inequitable access informed by poverty, and curricular silencing.

The Development of Discourse. The development of theoretical precursors for “achievement gap” discourse reflect the development of discourse in literature and policy. The Moyihan and Coleman report of the 1960s revealed disparity between groups, particularly those of socioeconomic and minority racial/ethnic identity. Following the wake of the Coleman Report (1966), Jencks and Phillips (1998) published *The Black-White Test Score Gap* which really began with collective inquiry. Four years prior, Herrnstein and Murray released *The Bell Curve*,

eliciting vibrant discourse around cognitive skills. They believed genetic inequality could explain cognitive inequality, and that this could even partially explain the test score gap between Black and white students (Herrnstein & Murray, 1994). In response, Jencks collaborated to help support a workshop at the University of Chicago where one day was dedicated to studying causes of the test score gap between Black and white students. Papers produced from the workshop revealed wide and controversial conclusions, and thus, *The Black-White Test Score Gap* was inspired (Jencks & Phillips, 1998).

Jencks and Phillips argued the test score gap was not “an inevitable fact of nature” (p. 2), through the lack of evidence that Black students genetically possess less intellectual capability. Instead, they explored various educational, psychological, and cultural explanations, and—counter to the Coleman Report—how school resources impact achievement (Jencks & Phillips, 1998). Contributed chapters articulate the complexity when analyzing the test score gap. Such complexity includes racial bias in testing (Jencks, 1998), family background (Phillips et al., 1998), teachers perceptions (Ferguson, 1998), stereotype threat (Steele & Aronson, 1998), and burdens of “acting white” (Cook & Ludwig, 1998). This “landmark collection of essays” (Chambers, 2009, p. 417) tackled issues of inequitable access in the education system curving discourse to explore beyond racialized and innate differences in achievement.

While *The Black-White Test Score Gap* (1998) serves as a pivotal piece of literature framing “achievement gap” discourse in the U.S., it does not coin the term—similar to the Coleman Report (1966). Not once is the term “achievement gap” referenced in the index (Chambers, 2009). Use of the term alone seems to counteract progress made by Jencks and Phillips insinuating the problem is the students, and more specifically, students of color. This

avoids placing responsibility on the educators, school, and structural institutions at large (Chambers, 2009). The “achievement gap” reform to follow, while intentional in addressing inequity, is based on the implication that White students perform better on standardized tests due to ability and effort, snowballing years of work from a student deficit perspective.

#### Examination of “Achievement Gaps” in Montana

National “achievement gap” policy and literature focus primarily on Black and Hispanic identities as students of color compared to their white peers, yet Montana is not exempt from the continuation of discourse. Across the last decade, the enrollment of Black or Hispanic students has remained less than 10,000 in Montana, however across the same timeframe, students recognized as Native have exceeded an enrollment count of 20,000 each year. White students encompass the dominant racial student population in Montana, but Native students consistently form the second largest racial student population at over 15 percent of the total enrollment count (GEMS, 2023b). Most states examine Black-white test score discrepancies and “achievement gaps.” Montana similarly has defined policy and mandates reporting examining differences between Native students and their non-Native peers, often referring to the “achievement gap” for Native students. Most notably, Montana participates in “achievement gap” discourse and policy through the American Indian Achievement Gap Payment and the *American Indian Student Achievement Report*, both products of NCLB. In addition, Indian Education for All provides funding to schools which meet the requirements and reporting regulations (MCA 20-1-503).

American Indian Achievement Gap Payment. It is important to consider the emergence of “achievement gap” discourse and terminology in the context of education reform in order to fully grapple with the consuming role it has played in schools. Since the emergence of NCLB,

massive federal dollars have been invested into addressing “achievement gaps” in U.S. schools. In Montana, an estimated \$45 million has been invested over the last 15 years to address the state’s recognized “achievement gap.” In 2007, five years after the release of the NCLB education reform, Montana codified the “American Indian Achievement Gap Payment” providing finances to public school districts for the purpose of narrowing the achievement disparity between Native and non-Native students, amended in 2013, and most recently in 2021 (20-9-330, MCA). Using the October snapshot enrollment counts, payment is calculated using the number of students who identify as American Indian. As a requirement of receiving payment out of the general fund, the OPI is responsible for reporting on standardized test scores, graduation rates, and dropout rates to the governor and Legislature on a biennial basis (20-9-330, MCA). While the original title of this report was the *American Indian Student Achievement Report*, it has adapted to more common– and on occasion formal– referral as the “American Indian Achievement Gap Report.” This biennial report has thus seen several publications in recent years. The gross national and local financial investments alone demonstrate the grip “achievement gap” efforts have on the educational system without considering the time of teachers, administrators and school leaders, state and federal decision makers, and researchers in documenting, analyzing, and responding to identified gaps. In this way, formalizing the concentration of abundant efforts, research, and payout in a historically short period of time.

American Indian Student Achievement Report. The “Achievement Gap Report” in Montana must follow the guidelines provided by the Montana Code Annotated (MCA) for other reports to the Legislature. While this dictates some logistic aspects such as abstract length (5-11-210, MCA), it also has restricted the report from adapting from its origin. In this way, every two

years OPI produces a report which highlights the change in “achievement gap” between Native and non-Native students using assessment, graduation, and dropout data (OPI, 2018; 2020a; 2022). In accordance with SPD 15, Montana student race data are collected using the federal standards (DOI, 2021) where students who identify as Native are provided only the option of American Indian or Alaskan Native to identify with. These standards provide little flexibility for students who may identify with more than one race, and certainly inadequately acknowledge oppressive identities forced by this category and term. While still with limitations, the report attempts to include all Native students by utilizing both students who identify as American Indian and Multiracial as a conglomerate racial category of Native (OPI, 2018; 2020a; 2022). The “Achievement Gap Report” and the American Indian Student Achievement Dashboard (GEMS, 2023c) are the only two places of presented data through OPI which utilize this category.

The most recent Report includes statewide assessments from the 2021-2022 school year for grades 3-12 including the Smarter Balanced assessment (SBAC) in both math and ELA, as well as the ACT for grade 11 in ELA and math. Using these proficiency rates, the gap in achievement between Montana Native students and their non-Native peers is visible (OPI, 2022). Comparison to past reports display a similar and historic trend (OPI, 2018; 2020a, 2022) Further, examination of current data (GEMS, 2023d; GEMS, 2023e) displays the continuation of this disparity. In this way, the disproportion in achievement between Native students is demonstrated three ways: (1) Native students perform at lower proficiency levels where over 50% are identified as novice on both math and ELA state assessments 3-12, (2) Montana schools with the highest populations of students who identify as Native have lower performance on state

assessments, (3) Native students graduate at lower rates (71.35%), and dropout at higher rates (6.63%) than their non-Native peers (2.78%).

Montana is a predominantly rural state with little diversity compared to other states (Showalter et al., 2023). The student population is predominantly white— 77.5 percent— but Montana also has a significant Native student population at 15 percent (GEMS, 2023b). While most states examine “achievement gaps” between Black and white students, or Latina/o and white students, and often geographically for urban and suburban districts, Montana is unique in both demographic and geographic context of its students and schools. Yes, this unique context means one area of focus for inequitable educational opportunities is better understanding the disparity between Native and non-Native student success. However, similar to national trends demonstrating stagnation in “achievement gaps” narrowing (Boykin & Noguera, 2011), the “Achievement Gap Report” highlights little evidence that either the data used to measure achievement, nor the efforts set in place to close the gaps, is effectively providing a solution. Perhaps similarly, despite historical and continued implementation of Indian Education for All, Montana educators struggle with effective depth in implementing its curriculum. What cascades in the current scenario is an emphasis on student deficit reporting, curriculum and instruction— which intends to hold schools accountable in honoring Indigenous peoples, cultures and histories but required a lawsuit and House Bill to articulate an existing shallowness— that can superficially provide Indigenous voice, and a complex reality navigated by Native students.

Indian Education for All. Montana holds a unique responsibility through the 1972 Constitution (Article X, Section 1(2)) which recognized the distinct cultural heritage of Indigenous peoples and importance of educating all Montana students on the history and cultures

of each Montana tribe. In 1999, the 56th Legislature passed House Bill 528 forming what is now commonly known across Montana classrooms as Indian Education for All (IEFA) (MCA 20-1-501). In 2005, Legislature provided funding to support the efforts of IEFA in Montana classrooms as Implementation Grants to school districts offering about 3.5 million in funding annually (NARF, 2023). Since 2006, the OPI has offered model lessons, books, videos, and other instructional materials across content areas (Juneau, 2001) for adequate implementation across classrooms. More recently, House Bill 338 made its way through the House and Senate enhancing the reporting requirements for schools that receive IEFA funds (HB0338). Through Article X, equitable education is guaranteed to all students— a responsibility held with integrity and pride as the first state that constitutionally obligates educational systems to include Indigenous people, history and culture within its educational content and goals. Not only does IEFA enrich instruction and learning, “*Indian Education for All* is the law,” (Elser, 2010).

Montana’s Constitution provides grounds for the state’s education institutions and programs including: Board of Public Education, the Office of Public Instruction, and the Office of Higher Education. Through IEFA, these State programs, Montana’s tribal nations, and the Board of Regents are committed to (1) providing opportunities in schools for all Montana students to have awareness and understanding of the unique culture, heritage, and contemporary issues of Indigenous peoples, (2) providing educators with opportunities of training to be prepared to teach the unique culture, heritage, and contemporary issues of Indigenous peoples, (3) supporting the recruitment and retention of Native teachers, (4) providing a model curriculum approved by the Montana Advisory Council on Indian Education (MACIE) and to make it available to all K-12 public schools, and (5) providing professional development ensuring

Montana educators have opportunities to learn about Indigenous culture, heritage and contemporary issues for their preparation in providing leadership and instruction (Juneau, 2001).

The OPI has established a number of initiatives to meet the legal mandate of IEFA. Functioning as a backbone is the “Essential Understandings Regarding Montana’s American Indians” which includes seven elements as guiding principles behind IEFA. These guiding principles have not only supported Montana education, but similar efforts in other states such as Maine, South Dakota and Colorado. Another initiative is the incorporation of IEFA into the Montana Content Standards. In 2011, Montana adopted the Common Core State Standards integrating IEFA into social studies, science, reading and math (Juneau, 2001). For Montana educators, not only is IEFA the law and required of their classroom design, but an abundance of resources for implementing IEFA are available through the OPI assisting the enriching of curricular and pedagogical choices. Organized by IEFA curricular leaders at the OPI and in collaboration with tribal communities, lessons and resources are continuously developed and made available to Montana public schools. In addition, a new Montana history textbook was released under the leadership of Krysl Holmes and historian Dave Walter (Holmes, Dailey & Walter, 2008), and collaboration projects such as the twelve-episode video series titled *Montana Mosaic: 20th Century People and Events* made with the Montana Historical Society (MHS, 2014) offer multiple modes for introducing material.

IEFA scholarship (Carjuzza et al., 2010; Deyhle & Comeau, 2009) recognizes the unique opportunities of Montana’s IEFA policy and development as a “bold and audacious multicultural education reform strategy that situates tribal nations and public schools on equal footing, making Native peoples partners in the education of all students” (Hopkins, 2020, p. 7). Some research

has explored tangible success measures, such as how IEFA has successfully influenced Native student achievement and culturally responsive teaching (Carjuzaa, 2012a; 2012b). Other research has focused on the efficacy of IEFA to expand curriculum in public schools with Indigenous languages and values (Carjuzaa et al., 2015; Carjuzaa & Ruff, 2016; Carjuzaa, 2017). Montana's opportunities through IEFA require collaboration between tribal communities, educators, and curriculum leaders functioning from an inclusive framework between Native and non-Native groups on Indigenous education reform over curricular and pedagogical choices (Hopkins, 2020). These opportunities, while effective and in many ways novel, are not excused from pain points as inclusive frameworks also find a need to embrace *decolonizing conversations* (Hopkins, 2020) in a discourse of Native student success.

Despite efforts, the ease and authenticity of classroom implementation has been in question for some Montana districts— perhaps illuminating that despite policy, intensive curriculum development and resources, and even the often healing element of time, that the effective weaving of Indigenous voice, culture, heritage and contemporary issues is an effort of swimming upstream. Perhaps illuminating that not unlike redefining the “achievement gap,” the narrative of Native student success is larger than policy. Not to be interpreted that policy is an ineffective or unnecessary tool in Indigenous education and measuring Native student success, or that IEFA is not an innovative multicultural education strategy. Rather, that the American education system is wrought with a habitual norm of accepting structural inequity where the dominant curricular voice is a white, male standard (Swartz, 1992) and methods for measuring student success fundamentally function from a student deficit model. Without an approach that interrogates colonizing history and the crafting of reform to dismantle the perpetuated structures

that disease public schools, “the law risks reproducing a colonizing, assimilative process” (Hopkins, 2020, p. 9) that limits Native student success to the confines of the same colonized and assimilative box.

The need for decolonizing Indigenous education in Montana public schools amidst the successes of IEFA can be examined in a recent lawsuit presented in 2021 against the OPI. Yellow Kidney et al. pursued action against OPI by articulating failure to uphold implementation of IEFA across all Montana public schools or require school reports detailing their spending of IEFA funds (NARF, 2023). Grounds for this lawsuit rests in the State’s insufficient school-level tracking of IEFA funds making pursuit against individual schools challenging. While many schools and Montana educators are dedicated to establishing a depth of IEFA implementation into their curricular and pedagogical choices, the habitual norm of accepting a colonized classroom of white, male dominance and a student deficit lens is challenging to swim upstream against. Despite access to lessons and resources, opportunities for professional development, and even funds to support implementation, Montana schools face a need for accountability practices.

In the spring of 2023, the intention of House Bill 338 was to hold Montana public schools accountable for curricula appropriate spending of IEFA funds. The proposed amendment would weaken the mandate of Article X through the language change of IEFA as a “requirement” to an “encouraged” recommendation in Montana schools. Representative Jonathan Windy Boy called on the accountability of state funds requiring a more strict reporting system of IEFA curricula expenditures further addressing a lawsuit filed in 2021 against OPI and the Montana Board of Education (Wagner, 2023). Windy Boy introduced HB 338 to address scattered requirements of IEFA curriculum implementation in many Montana schools and uphold a more rigorous process

of reporting from public school districts to clarify the curriculum is taught with fidelity. This House Bill was signed into law in May of 2023 (MTFP, 2023). While the curriculum and district-level reporting procedures surrounding IEFA do not directly contribute to the discourse of “achievement gaps” in the same way as the Gap Payment and the *American Indian Student Achievement Report*, upholding IEFA and curricula accountability of Montana schools helps paint the challenges and opportunities Native students have navigated in erasing a student deficit perspective from their academic history and potential.

Montana educators hold a legal, ethical and instructional responsibility to implement IEFA in their classrooms (Elser, 2010). A responsibility which became law over five decades ago, and yet, too many Montana educators and classrooms currently wrestle with the Essential Understandings and falter by including IEFA curriculum at a “relatively superficial level” (Elser, 2010, p. 4). The recent work of HB 338 illuminates a reality where many Montana schools not only touch the curriculum superficially but require stricter reporting procedures to prove depth of implementation. Across Montana classrooms, this bill seems to articulate how the Montana public school as a system perpetuates colonized inspired curriculum as only years of mastery lead to appropriate depth in implementing IEFA by educators. Rather, even in a state that has historically upheld the education of its Indigenous people, cultures and histories through policy, many of its schools still gravitate to shallow content, of course simultaneously aligned to student deficit “achievement gap” patterns in reporting. Montana Native students navigate a classroom reality different from their non-Native peers where even in a state that intentionally has created policy to weave Indigenous voice into the curriculum, these same classrooms require

accountability of implementation and can function from an implicit bias of assuming Native student deficit in performance and success.

Defining Native Student Success. Native student success must be twofold: both in the way students are educated and in the way their success is measured. Considering first the way Native students are educated: “To address the achievement gap, low test scores, the connection between Native students and the public schools, and the persistent social and economic disparities among Native youth... [we] need to radically shift the way [we] think about and do Indigenous education in public schools” (Hopkins, 2020, p. 10). It is important to make distinct the difference between *Indian schooling and Indigenous education* (Hopkins, 2020; Pratt et al., 2018). The experience of formal schooling such as “lecturing, classroom discipline, and standardized testing” (Brayboy & Lomawaima, 2018, p. 84) is “institutionalized and systematically governed and legislated by provincial, state, or federal institutions... [and] bounded within physical structures where the majority of learning is confined to specific temporal, legislative, and bureaucratic limitations” (Pratt et al., 2018, p. 4). In many ways, Indian schooling ideates within intentions of colonization– colonization of mind, body, and land– evident in Indian boarding schools, as well as intentions of assimilation which can even be examined today in standardized testing (Lomawaima & McCarty, 2006; Reyhner & Eder, 2017). In stark comparison, Indigenous education “refers to how Native peoples have survived and resisted this colonizing, assimilative agenda by asserting their sovereign right to educate their children according to their own cultures, languages, and knowledges” (Hopkins, 2020). Indigenous education is a political movement of resisting, also referred to as *decolonizing education* (Pratt et al., 2018; Hopkins, 2020). Brayboy and Lomawaima (2018) describe the

meeting place of Indian schooling and Indigenous education as “a battleground between sovereigns” (p. 83), and further a *battleground* where “knowledge systems, knowledge production, cultural values, and children’s lives are on the line” (p. 83). The process of decolonizing education acknowledges the pervasiveness and normalcy of racism (Delgado & Stefancic, 2012) and colonization (Brayboy, 2005) in the American education system and acknowledges the need to untangle their silent structural reality in classrooms.

Native student success must also approach the way success is measured. Through the requirements of the Achievement Gap Payment and the *American Indian Student Achievement Report*, Montana Native students’ success is measured using academic achievement and completion measures where achievement is success on standardized assessments. Not only can underpinning intentions of assimilation be examined in standardized testing (Lomawaima & McCarty, 2006; Reyhner & Eder, 2017), but three iterations of the biennial report (OPI, 2018; 2020a; 2022) show these measures do very little to demonstrate the success or the growth of Native students in stagnant or even widening gaps. At the most recent RISE Conference hosted by the OPI, Montana Native high school students grappled with what success looks and feels like outside of achievement scores and completion rates. These students emphasized the importance of the school environment to incorporate cultural values, language, and opportunities for collaboration. In this way, students defined success not as a metric but rather the unique relationship students cultivate with their Native identity throughout their academic journey to celebrate authenticity and pursuit of self-discovery (RISE, 2022).

While the way Native student success is measured for policy and reporting measures may not embrace the expression of students at the RISE conference, the way disparity is defined may

tangibly face modification to more accurately reflect factors such as school environment and opportunities. Within the context of understanding “achievement gaps” by racial disparity, it is assumed achievement is due to the child’s lack of ability or motivation to meet adequate achievement scores or successfully graduate. Often neglected is considering how gaps in achievement are simultaneously informed by systemic, structural inequalities catalyzed by the role of history. In this way, “achievement gaps” are better represented when termed “receptment gaps” (Chambers, 2009) or “opportunity gaps” (Clausen et al., 2020).

#### A Case for Critical Examination of “Achievement Gaps”

Critical Race Theory (CRT) may guide the work of redefining “achievement gaps” as the framework enables a purpose of progress- directly for people of color, acknowledging that intersections of identity craft unique perspectives and experiences of their own, and indirectly for the more dominant White perspective and experience providing both awareness and criticism. CRT acknowledges racism and marginalization is a permanent, social construction accepted with normalcy, as evident in tangible structural inequalities such as racialized academic “achievement gaps,” wealth and income gaps, health and wellbeing gaps, etc. Adopting such a CRT framework is purposeful through methods centralized on experiential knowledge. In this way, storytelling becomes the backbone for narrative that is counter to the dominant perspectives and histories, in turn, exposing that truth is just as socially constructed as race is. Committed to progress through social justice outcome intentions, the work of redefining “achievement gaps” through CRT pursues an outcome of justice for all students. The purposeful narratives collected serve more than mere counter chords to a dominant melody, they are acts of resistance to a normalized silence: “Paradoxically, it is the act of resistance that is our triumph” (Taylor et al., 2016, p. 9). In

turn, it is the acknowledgement, voice, and “unmasking” (p. 18) unveiled to expose racism and intends for a societal structure in full awareness of racism's permanent presence and impact.

Within classrooms, schools, larger systems and policy, redefining “achievement gaps” through a CRT approach seeks to illuminate ways in which race and racism produce educational inequity— such as inequitable access to educational opportunities— within schools (Solórzano, 1997, 1998; Solórzano & Delgado Bernal, 2001; Solórzano & Yosso, 2001a, 2001b, 2002). Education in the U.S. lacks application and understanding of theory to identify the persistent presence of racial inequalities in academic achievement (Taylor et al., 2016). In this way, silence becomes the steady effort perpetuating racism and systemic, structural inequity within classrooms. Such silence is observed in curriculum, instruction, assessment, and funding. Too often, school curriculum silences voices and perspectives outside of the “master script” of the dominant white, male standard (Swartz, 1992, p.341). Further, race-neutral or colorblind approaches passively ignore (perhaps with ignorance) the existence of oppressive systems, racism, and inequity: “This race-neutral perspective purports to see deficiency as an individual phenomenon” (Taylor et al., 2016, p.25). With direct implications for understanding the “achievement gap,” CRT critiques assessment as a frequent tool used to legitimize student deficiency for students of color. And, with tangible implications on the organization of inequitable school spaces and geographies, CRT critiques school funding as a function of institutional and structural racism (Taylor et al., 2016). In this way, the spaces of schools must adopt intentional practice to acknowledge the normalized, and permanent presence of racism within the acts of learning (e.g. curriculum and instruction), the places of schools (e.g. school

geographies and funding), and the mechanisms of measurement (e.g. assessment and “achievement gaps”) by providing voice to the silences.

### Rationale for Redefining Gap Discourse

Academic “achievement gap” discourse functions from a student deficit perspective. The methods for collecting various data used are susceptible to racialized practice such as testing bias in standardized assessments and oppressive terminology in race categories. The comparative nature of measuring “achievement gaps” insinuates deficit is of the student, particularly students of color. Measurement of achievement, namely through standardized testing, in education is a product of systematic historically produced oppression. “A modern form of educational oppression, driven by deficit thinking, is high-stakes testing” (Valencia, 1997, p. 5).

Economically disadvantaged and minority racial/ethnic students additionally navigate a system that defines their success through these standardized assessments where educational obstacles to access and success already abound. NCLB (2002) launched a new norm of dependency on measurement through testing and SPD 15 (1977) spurred decades of “achievement gap” discourse limited by narrow frames of how the nation defines achievement and race.

Particularly in Montana, these standardized methods for categorizing race and measuring achievement have insufficiently highlighted the context and experience of inequitable access of Native students. Students who enter the classroom with historical and generational barriers of colonization and assimilation present in the structural institution that is their school system. Despite policy, practices, and places framed in outcomes of Indigenous erasure, the resilience and survivance of students persists— more dominant than any persisting gap. In the state of Montana, the commonly accepted “achievement gap” refers to the differences in academic

outcomes between Native students and their non-Native peers. However, similar to national perception, it is left unacknowledged by the abundance of inequalities which impact student performance (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010) making it racialized and from a student deficit lens. The American Indian Academic Achievement Report (commonly referred to as the “Achievement Gap Report”) reports only assessment and completion data to examine achievement outcomes of Native students. Efforts for redefining gap discourse in Montana might examine current racialized labeling through SPD 15 revisions, acknowledge the abundance of inequity Native students navigate, and simply stop calling it an “achievement gap” and rather adopt more representative terminology.

Native Student Racialized Data Analysis. *Native American* is a term that came to use around the civil rights movement in effort to utilize unbiased terminology (Dunbar-Ortiz & Gilio-Whitaker, 2016; Shear & Stanton, 2018). In similar effort, *American Indian* is often considered a “politically” correct term. *American Indian or Alaska Native* is the racial category articulated by SPD 15 as the standard in federal data collection and reporting (DOI, 2021). Unfortunately, both the terms *Native American* and *American Indian* function as titles for Indigenous Peoples and Nations that situates them dependent on the United States. Such terms “deny Indigenous sovereignty and self-determination” and “erase an essential history of acknowledgement for the peoples who lived on these lands long before the names American and United States ever existed” (Shear & Stanton, 2018, p. 8). Terms such as *Indigenous Peoples* attempts to remove connotation of American dependency, but still functions as a conglomerate identity effectively stripping unique and relational tribal affiliation and identity. Michael Yellow Bird (Sahnish, Arikara), quoted in Pewewardy (2000), articulates:

The terms indigenous and First Nations Peoples still generalize the identity of the more than 500 indigenous groups in the lower 48 and Alaska. However, I believe they are empowering ‘generalized’ descriptors because they accurately describe the political, cultural, and geographical identities, and struggles of all aboriginal peoples in the United States. I no longer use Indian, American Indian, or Native American because I consider them oppressive, counterfeit identities.

Montana students, through SPD 15 and general social acceptance, are categorized as American Indian— a conglomerate, U.S. dependent, sovereignty denying term.

During the 2022-2023 school year in Montana, 15,637 students (10.4 percent) identify as *American Indian or Alaskan Native* and 22,801 students (15.1 percent) identify as *American Indian or Alaskan Native or Multiracial* (GEMS, 2023b). Similarly, reports on the academic access and success of Montana Indigenous students are provided using the same terminology, such as the biennial *American Indian Student Achievement Report*. However, Native students in Montana may identify with (but are not limited to) Montana’s tribes including Crow, Northern Cheyenne, Sioux, Gros Ventre, Assiniboine, Chippewa, Cree, Blackfeet, Salish, Kootenai, Pend d'Oreille, and Little Shell Chippewa— each intrinsically linked to identity. These listed tribes capture those most often represented in Montana; however, it is important to acknowledge that Native students in Montana are not limited to these tribes, and students from tribes not listed here or from outside Montana may also be present.

Currently, Montana Native students are subject to reinforced social constructs of “American Indian” in data collected by their school, reported by their state, and standardized by their federal government. “Racial categories exist as subjective identifications... [a]s social constructions, they have changed over time, and yet they become reified and reinforced as they are used and reported by the federal government and researchers” (Croll & Gerteis, 2019, p. 56).

The proposed revisions to SPD 15 could potentially provide students the option of identifying

with additional categories, such as tribe specific categories, as long as they can be aggregated to pre-existing standards so adoptions between historical data series can be linked. In addition, fundamental concepts of how race is collected would be more closely aligned— recognizing race categories are sociopolitical constructs and are not an attempt to define race and ethnicity biologically or genetically (Initial Proposals for Updating SPD 15, 2023). The proposed SPD 15 revisions provide the self-identification flexibility attractive not only for Montana’s Native students, but identities across the country who may appreciate such option.

Utilizing the revisions to SPD 15 as leverage, redefining “achievement gap” discourse could adopt means of broadening the current confines of racialized measurement for Montana Native students. SPD 15, which is the current federal standard for how educational data is collected and reported by racial categories, is currently under the revision process. SPD 15 has not seen revision in over two decades, so the initial proposal and public comment period should have the attention and investment of stakeholders and state leaders. Particularly in Montana, the revisions contained within the initial proposal would allow Native students to potentially identify with additional categories, such as tribe orientation.

The effectiveness of opening self-identification beyond the current six categories however is not uncharted territory Montana must navigate. Research has begun questioning the subjectiveness of fixed racial and ethnic categories and classifications. Such work has identified variation in how researchers perceive and classify their subjects’ race, and how subjects self-identify (Boehmer et al., 2002; Brown et al., 2006; Harris & Sim, 2002; Roth, 2016; Vargas & Kingsbury, 2016; Vargas & Stainback, 2016). Saperstein (2012) argues in order for the complexity of racial identities to be represented, multiple measures should be collected by

researchers revealing how individuals' racial identity changes over time (Saperstein, 2012, 2013; Saperstein & Penner, 2012). In a study by Croll and Gertesis (2019), respondents were asked "What is your race?" and "Is there another ethnic category that you more closely identify with than [race]?" with the goal of better understanding the degree traditional categories of race reflect the self-identification of respondents.

This study found standard racial categories carry cultural latency as most respondents identified with a single, normative racial category (76.9 percent). This first finding suggests even when given open additional options, identification with one of the six pre-existing categories in Montana will be maintained for aggregation with historical datasets. However, this study also found while most respondents identified using normative categories, alternative racial categories were produced in the second question's response. In this way, when given the opportunity to provide an open response of self-identification, respondents provided an alternate identification (Croll & Gertesis, 2019). This finding reveals Native students in Montana may similarly be receptive of providing an alternative category such as tribe specific orientation. Implementation of such a flexibility could be as simple as adding an open-ended question after the federal race/ethnicity questions: *Is there another category that you more closely identify with?*

Providing an open-ended response may encourage a wide spectrum of alternative responses. While this certainly may pose the need for additional analysis and coding to better understand the relations and distinctions between self-identification categories, it would be a step in the direction of critically responding to the racialized reality of these categories with transparency in data collection and reporting. For example, respondents may choose a non-response. It should not be ignored that about 5 percent of respondents in the Croll and Gertesis

(2019) study chose to deny racial labels in the open-field question. This presents interesting inquiry around individuals who avoid racial classifications altogether, where perhaps there resides *colorblind ideology* (Bonilla-Silva, 2010) or *racial apathy* (Forman, 2004; Forman & Lewis, 2006) denying the importance of race, downplaying racial inequalities, and having indifference toward racial issues.

Adopting New Methods for Redefining the Gap. The adoption of new racial categories and open-ended responses, while led by well underway revisions to SPD 15, may take a while to be fully adopted at the local level. Redefining racialized gap discourse depends on the racialized naming strategies associated with data collection, however the state of Montana should not wait on SPD 15 to begin moving forward with other approaches for redefining the Native “achievement gap.” The *American Indian Student Achievement Report*— often referred to as the “Achievement Gap Report”— has been generated on a biennial basis. Allowing the use of this adopted term insinuates student deficit thinking, particularly of Native students, and displaces the responsibility away from the systems (i.e. OPI, schools). Furthermore, this report functions as a racialized “achievement gap” (Noguera, & Wing, 2006) comparing academic outcomes between Native and non-Native students. The report summarizes the success of Native students using performance scores alone and ineffectively illuminates the complex and various inequalities which inform the disparity in performance scores. Redefining the Native “achievement gap” could begin by adapting terminology back to its original form. Both formally and informally, reference to this report should be the *American Indian Student Achievement Report* rather than the “Achievement Gap Report.” Formally, this means ensuring the report and any affiliate production, such as the American Indian Student Achievement Dashboard (GEMS, 2023c),

remove any use of “achievement gap” terminology. If “gap” terminology is to be used, it should adapt to the “opportunity gap” (Clausen et al., 2020) instead.

Lastly, redefining Native “achievement gap” discourse in Montana must consider adopting the data exploration of various opportunity factors, or those factors which illuminate the inequity impacting achievement outcomes, in addition to performance metrics. The current report compares assessment performance, graduation rates, and dropout rates between Native and non-Native students. Various inequities impacting the disparity in achievement outcomes include access to quality educators, provision of quality teacher training, access to quality and relevant curriculum, adequate provision provided through school funding, access to technology and internet, consideration for disparity in wealth and family income, access to employment opportunities, access to quality and affordable housing, access to quality and affordable healthcare, nutrition, and childcare (Milner, 2010) to consider a few. Some of these areas of inequity are currently collected by the state, in which case redefining the gap in academic achievement through these measures is simply an effort of inclusion in the reporting. For example, the aligning performance scores and graduation rates, disaggregated by schools and districts, with: (1) spatially informed teacher quality data by supplying the count and rate of educators with class 7 licensure, (2) survey data collected during the COVID pandemic, providing insight to count and rate of households with access to internet and adequate bandwidth, (3) alignment to measures of poverty in neighborhood clusters spatially to school locations, and (4) count of meals served through National School Lunch Program data by school location.

Challenge will form around those areas of inequity not currently collected and reported, perhaps with insufficient data access. One example of such a factor impacting inequitable access is student mobility. While existing research articulates the impact of high student mobility rates on academic achievement (Astone and McLanahan, 1994; Crowder & South, 2003; Ingersoll et al., 1989; McLanahan & Sandefur, 1994; South et al., 2007; Straits, 1987; Swanson & Schneider, 1999, Teachman et al., 1996; Welsh, 2018, 2017) and local stakeholders in the field have expressed Montana Native student mobility as a significant opportunity factor (Clausen et al., 2020), the state has little understanding of what student mobility trends exist— particularly for rural school communities— and how those trends impact academic access. Movement forward must acknowledge inequity of space and inequity of resource for Native students in Montana to better understand the disparity in academic access and success.

### Inequity of Space for Native Students

Inequity of space is historically and geographically defined. In Montana, the forced flow of Indigenous peoples from Native lands to reservation lands, to the rigid drawing of poverty borders around these reservation lands, communicates structural and institutionalized stories of power and place. A critical spatial analysis of educational inequity considers historical, social and spatial experiences of students. Further, such critical awareness to the inequity of space in schools reveals how power is structurally inscribed and reinforced. The contextualized histories of power and place in Montana, particularly for Indigenous peoples, includes political policy such as land reform, as well as efforts of colonization and assimilation such as school reform. A map of Montana, her border lines of reservations, of school neighborhoods, and of income divides cannot be left to speak for itself. Embracing a critical analysis of space to better

understand disparity in academic outcomes of students, poverty and mobility are examined under the lens of functioning as student experiential factors defined by their histories, patterns and trajectories of space inequity.

### Critical Analysis of Space and Relationship to Opportunities

As a branch of CRT, Critical Race Spatial Analysis (CRSA) is an explanatory framework and methodological approach that accounts for the role of race and racism in geographic and social spaces. Identifying racism across geographic contexts, CRSA seeks to spatially analyze the structural and institutional factors associated with power and place (Solórzano & Velez, 2016). CRSA is interested in “how structural and institutional factors divide, constrict, and construct space” (Huber, 2008, p. 168) further impacting student academic experiences based on race. CRT provides the overarching theoretical framework for how CRSA understands space: “[S]chools and their varied spaces are intimately connected, so much so that a critical investigation of schooling and student experience, especially the role of race and racism, necessitates a sensibility to issues of spatial location and process” (Vélez & Solórzano, 2017, p. 11). A critical spatial analysis of educational inequity requires the interrogation of historical, social and spatial experiences of students, and how power is inscribed and reinforced within the mechanisms of schools to produce social inequity. Furthermore, it identifies that educational inequities are the result of the unjust geographies of public schools which are placed at the intersections of space, power, and knowledge (Morrison et al., 2017, Soja, 2010).

Through critical examination of race, space and schools, CRSA of educational environments aligns to the tenants of CRT in various ways. By foregrounding the color-line (DuBois, 1903/1999) CRSA examines closely the relationships between race, racism, history and

space. As a guiding framework CRSA also emphasizes the analysis, critique, revision, and creation of mapping spatial places and experiences while aligning to social-spatial narrative. CRSA is a tool for telling *contextualized counter-cartographic narratives* (Knigge & Cope, 2006) about the importance of race and racism. Similar to how critical quantitative approaches refuse to allow data to speak for itself, CRSA refuses to allow maps to speak for themselves as the socio-spatial relationship between race and space is informed by history and shaped by the cartographer (Solórzano & Velez, 2016). And lastly, that critical cartography in action should and can take the form of social justice (Morrison et al., 2017). In this way, a commonly accepted tool in CRSA is the digital mapping technology known as geographic information systems (GIS). GIS is used to explore the geohistorical and geopolitical markers of race and racism in maps, and use GIS mapmaking to produce counter-cartographic maps and narratives (Morrison et al., 2017).

In alignment to “achievement gaps” and inequitable access, utilizing CRSA as a guiding framework “makes visible the fingerprints of white supremacy in shaping every urban and rural neighborhood” (hooks, 1990, p. 14). The collection and reporting of “achievement gaps” is concerned with gaps between districts, schools and neighborhoods. Robust qualitative methods exist for CRSA which are applicable to unveil the influence of oppressive social structures on inequities informing “achievement gaps,” but quantitative CRSA is effective as well. Because “[h]uman spatiality in all its forms and expressions is socially produced” (Soja, 2010, p.103), one area of focus quantitative CRSA researchers– and similarly critical quantitative researchers– take is the construction of racial categories. “When racial statistics are interpreted or discussed, race is very often treated as if it were *a cause of*, rather than merely a *factor associated with*, social phenomena” (Austin, 2008, p. 307). In addition, *spatial data* are any data with a spatial

component, usually a location (Morrison & Garlick, 2017). For example, the latitude and longitude of a school is spatial data. Knowing spatiality is socially produced, and race is socially produced, quantitative CRSA analyzes the socio-spatial relationships between race, schools, and achievement by illuminating how geographies both contribute and resist inequities. In Montana, this requires not only critically exploring opportunity factors' impact (e.g. student mobility and poverty) on academic access and success, but also how these factors are situated spatially. One starting point for seeking spatial justice within "achievement gap" discourse for Montana may be in exploring the influence of opportunity factors on academic outcomes by the spatially informed spaces of school locations.

#### Political Organization of Space: History of Land Reform for Indigenous People

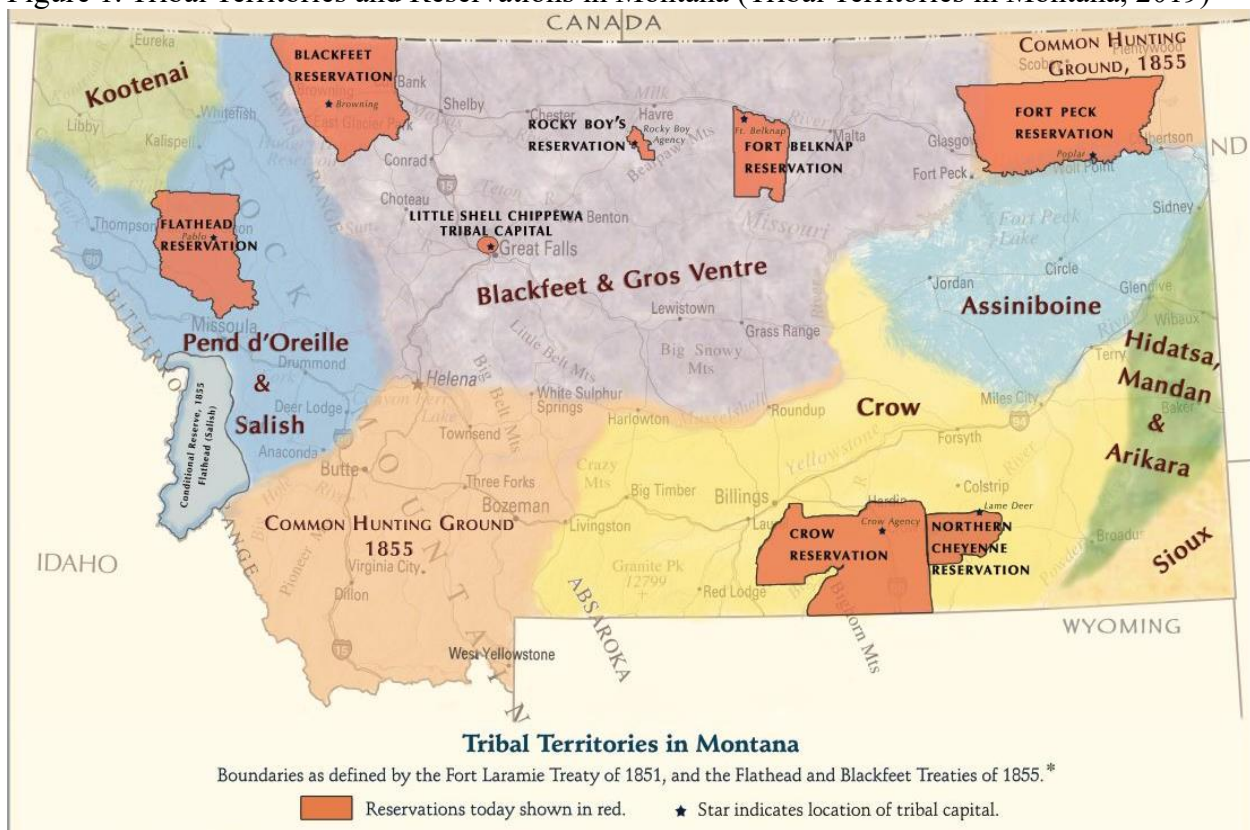
Long before racial categorization standards, and the current spaces of school locations, inequitable access for Native students' education in the U.S. begins with the realities that colonization is endemic to society and assimilation is intimately linked with governmental policies toward Indigenous people (Brayboy, 2005). Early policy removing and controlling Indigenous relationships with their traditional lands are catalyzed by a drive for assimilation of Native people. The removal of Indigenous people from lands and the formation of reservations in the U.S. serve as demonstrations of intrusive political organization of space resulting in real and imagined geographies of colonized power in the nation's history (Soja, 2010). Such socially produced geographies are a means for institutionalizing racial segregation and epitomized a scenario of the colonizer versus the colonized, an institutionalized and structural consequence evident in schools today.

Prior to the Revolutionary War, the majority of the American people lived within a few hundred miles of the Atlantic Ocean. By 1840, one-third lived between the Appalachians and the Mississippi River. As settlers' movement continued to encroach Native territory, the federal government took on more direct land policy (Urban & Wagoner, 2014). In 1830, the Indian Removal Act approved the forceful removal of Indigenous peoples under the Jackson presidency. Under ideals of *progress* and *Manifest Destiny*, forced migrations were rationalized for the sake of American expansionism. While based on consent, many were removed in chains and handcuffs. Between 1835 and 1838 alone, over 2,000 Cherokee died along the "Trail of Tears" as they were forced to land west of the Mississippi (Utter, 2001). Removal functioned as a traumatic organization of space in an attempt to separate their ways of knowing, and to colonize the "uncivilized" separate from norms of white, Euro-centric, Anglo-Saxon expansion.

From 1850-1887, federal policy focused on the movement of Indigenous peoples westward into unsettled territories. Policy was pursued establishing Native reservations by treaty. Treaties wrought extensive impact through restriction including the loss of homeland base (e.g. food and medicine sources), catalyzed economic dependency on the U.S. government, and isolated learning opportunities eventually leading to boarding schools (Price, 2011). The U.S. government held unbalanced power, such as the treaty of 1855 with the Flathead, Kootenai, and Salish tribes where eventually in 1872 Congress ordered their removal to the Flathead Reservation (Charlot, 1876). Today, Montana has eight federally recognized tribes and seven reservations defined through the Fort Laramie Treaty of 1851, and the Flathead and Blackfoot Treaties of 1855 (see Figure 1). The political organization of space through reservation assignments established physical boundaries that enforced racial segregation and consolidated

colonial power. These reservation boundaries were not merely lines on a map; they structured socio-economic conditions and limited access to essential resources, such as education, healthcare, and economic opportunities. This spatial division laid the groundwork for enduring systemic inequities that continue to affect Native communities today, where the effects of these historical policies are still visible in persistent disparities.

Figure 1. Tribal Territories and Reservations in Montana (Tribal Territories in Montana, 2019)



In 1887, the Dawes Allotment Act instigated further loss of land, breakdown of tribal unity, increased assimilation to dominant white culture, and increased economic dependency to cash economy. The Dawes Allotment Act (1887) divided reservation lands into 160 acre lots to be claimed by male household heads. The effort was to end the common ownership of tribal

land. If lots were unclaimed, they could be assigned by the government to non-Native owners. By 1934, two-thirds of reservation lands were lost (Price, 2011; Fernlund, 2011). Unfortunately, the relationship of federal government policies and Native lands continues through history as a reality of how colonization and assimilation function as fundamental structures of inequity.

Through an interrogation of the historical, social, and spatial consequences of early colonization, revealed is the inscribed and reinforced power within the mechanisms of schools (and other structural spaces) to produce inequity. Furthermore, educational inequity for Native students becomes a result of the unjust geographies of public schools which are placed at the intersections of space, power and knowledge (Morrison et al., 2017, Soja, 2010). The lived land-related history of removal, colonization, and assimilation for Indigenous people demands a generational and collective action of resilience. Sabzalian (2019) captures the concept as survivance, or a combination survival and resistance. In this way, it attempts to capture the creative means of Indigenous people after lived trauma such as genocide and colonization (Sabzalian, 2019; Morrill, 2017). An examination of pivotal points contributing to inequitable access of Native students can begin nowhere other than these histories of colonization and assimilation as their survivance is integral to interpreting academic access and success today.

### Spatial Consequences of Early Colonization and Assimilation

Native students in the U.S. face unique complexity through centuries of assimilation contributing to structural inequality within schools as massive instruments of colonization where erasure continues to function as an obstacle to equitable academic experiences. Daniel Wildcat challenges that there is no other group of people in America who have faced the forces of identity assimilation to dominant society more than Indigenous people (Deloria & Wildcat,

2001). Native students' history of assimilation functions as a foundational contribution of inequitable access for their educational access in today's schools and classrooms.

Rich culture, established societies, and valuable educational practices existed in North America long before European "discovery." Children were educated through generations of concentric circles of teachers, where concepts of family extended to the tribe and instruction embodied storytelling and oral tradition. However, European norms quickly became dominant (Urban & Wagoner, 2014). Indigenous cultures, languages, and educational practices became "savage" forms: "Although the European colonizers had much to learn, from the outset they assumed the role of master" (p. 9). European norm became more dominate on Native communities in attempts to indoctrinate white culture. In the wave of Enlightenment, the birth of common schools emphasized a unified education to simplify language to the dominant English dialect, and stressed the moral, cultural, and historical dominance of Anglo-Saxton tradition (Urban & Wagoner, 2014). This fundamental shift in education reform plated potent seeds for the reality of assimilation through American Indian boarding schools.

Post-Civil War, federal policy regarding the education of Native children became concerned with assimilation by "saving" them from their "uncivilized" reservation living and tribal schools (Urban & Wagoner, 2014; Utter, 2001). Federal policy approached with two avenues of reform, both of which were strategies to separate Native people from their culture: land reform and education reform. Richard Henry Pratt received permission to open the first off-reservation boarding school in 1879, Carlisle Indian School, where the adopted mission was: "Kill the Indian and save the man" (Utter, 2001, p.309). With goals of giving Native youth a new identity, students were stripped of their Indigenous self by the cutting of hair, dressing of

uniforms, changing names, banning use of Native tongue, and forcing a world of lines, corners, and squares (e.g. desks, straight rows) rather than worldview of circular phenomena (e.g. sun, moon, sacred hoop) (Urban & Wagoner, 2014). The assault of orchestrating new identity for Native children became a felt trauma, additionally often met with physical punishment.

The assimilation of Native children through education reform continues to contribute to the current context in education. History articulates *Indigenous erasure* through federal policies of removal and assimilation. There is also embedded quieter assimilation where *Indigenous erasure* (Sabzalian, 2019) in classrooms and schools today find settler colonialism rooted in a “logic of elimination” (Wolfe, 2006, p. 387). Settler colonialism manifests where “teachers disregard Indigenous students’ perspective, privilege Eurocentric curriculum, commodify and objectify Native culture, absorb Indigenous students into multicultural frameworks” (Sabzalian, 2019, p. xiii). There is a reality of colonial contexts in U.S. public schools and endemic structures in society more generally which constrains Native educational self-determination (Brayboy, 2005). Inequitable access of Native students’ education is shaped by centuries of assimilation where both historical trauma (Brave Heart 1999; Brave Heart & DeBruyn, 1998) and generational trauma (Thoreson et al., 2020) impact their academic experiences.

As spatiality and race are socially produced, the histories of colonization and assimilation for Montana Indigenous peoples must have value in understanding the socio-spatial relationships that exist today between race, schools and achievement for Montana students. While maps cannot speak for themselves, they specially illuminate how geographies both contribute and resist inequity for students. In particular for Montana Native students, historically produced reservation lines simultaneously define how opportunity factors such as neighborhood and

school-level poverty contribute to inequity while *also* serving as harbors of culture, relationships and self-identity for Native students. Spatially exploring opportunity factors' impact such as student mobility and poverty on academic success can pivot from deficit perspectives regarding "achievement gaps" to instead acknowledge how these factors spatially inform spaces of school locations. In this way, it is not only the spaces, but also the inequity of resources within these defined spaces.

### Inequity of Resource for Native Students

The inequity of resources prevalent not only for Montana Native students, but nationally students from high poverty and minority homes, includes an abundance of experiential factors including "the teacher quality gap, the teacher training gap, the challenging curriculum gap, the school funding gap, the digital divide gap, the wealth and income gap, the employment opportunity gap, the affordable housing gap, the health care gap, the nutrition gap, the school integration gap, and the quality childcare gap" (Milner, 2010, p. 9). Educational inequity is observed in the continuation of students from the most privileged backgrounds continuing to dominate educational opportunities and is a significant enduring social problem that continues to be examined extensively in social science research (McMaster & Cook, 2019). This paper cannot explore the expanse of inequity with integrity, and instead focuses on the impact of poverty and mobility, at both the individual and school levels, on academic achievement. The two factors of poverty and mobility are irrevocably linked to histories and outcomes of school location, segregation, and integration, further evolving then into factors requiring geographic context to grapple with the impact on student success measures and experiences. School conditions, including its location, student population, access to resources and quality educators, etc.

influence students' success. The histories defining the boundaries and borders that define school-level poverty frame the story of resource inequity. To inquire how disproportionate outcomes are driven by these histories, one must ask how disproportionate outcomes are driven by racism. Embracing a critical analysis of quantitative methods to better understand disparity in academic outcomes of students, poverty and mobility are examined under the lens of functioning as student experiential factors defined by their histories, patterns and trajectories of resource inequity.

#### Critical Analysis of Quantitative Methods for Examining Racialized Outcomes

Underneath the umbrella of CRT, Quantitative Critical Race Theory (QuantCrit) seeks to challenge and improve the use of data through application of a CRT framework (Castillo & Gillborn, 2022) to unveil inequalities in our education system (Solórzano & Ornelas, 2002; Solórzano & Villalpando 1998; Solórzano & Yasso 2002). QuantCrit buds from CRT through five principles: (1) the centrality of racism, (2) numbers are not neutral, (3) categories are not natural, (4) voice and insight, or that data cannot speak for itself, and (5) a social justice and equity orientation (Gillborn et al., 2018). As CRT is closely aligned with qualitative methods, the challenge of QuantCrit is application of CRT insight through quantitative methods, where the strictly objective nature of numbers is the critique (Airaksinen, 2018). However, since the mandates of NCLB (2002), increasing amounts of student data are reported every year at the federal, state, district and local level. This provides access to extensive data, but “simply providing statistical data is no guarantee of transparency” (Castillo & Gillborn, 2022). Instead, QuantCrit embraces an active role understanding quantitative data function at the core of how race and racism is produced, legitimized and perpetuated in education (Crawford, 2019).

QuantCrit neither accepts that numbers are strictly objective nor that data is naturally transparent, rather it seeks to dismantle how racism influences quantitative data collection and analysis (Castillo & Gillborn, 2022; Gillborn, 2019).

Castillo and Gillborn (2022) explore the five aligned tenants of QuantCrit with suggestions for quantitative researchers providing a tangible roadmap for navigating the theory. The first tenant of QuantCrit is in step with the heart of CRT as a whole by accepting the centrality of racism. This alignment encourages the creation of a positionality statement by researchers, which is standard in qualitative work but often harder to find in quantitative work. In addition, deficit thinking can be avoided by framing survey questions with an asset-based perspective. The second tenant, that numbers are not neutral, counters the assumption quantitative data is free from bias. Caution to quantitative researchers includes careful selection of the denominator and model used in the study. CRT articulates that race is a social construct, and QuantCrit embraces the third tenant: categories are not natural. In this way, categories of race in quantitative research should be approached critically. One suggestion is to substitute “race” with “racism” whenever race/ethnicity categories are measured (Gillborn et al., 2018). In application with “achievement gap” discourse, this changes the question from *how are disproportionate outcomes driven by race* to *how are disproportionate outcomes driven by racism?* The fourth tenant cautions allowing data to speak for itself as all social research is shaped by the researcher. This requires collecting perspectives and participation, being transparent with the limitations of a study, and providing context in alignment to statistically significant results. Lastly, QuantCrit seeks to empower quantitative researchers with a social justice and equity orientation when

communicating results. In this way, a researcher's interpretation of results should acknowledge ways racism may be at play, even in the metrics utilized (Castillo & Gillborn, 2022).

The emerging field of QuantCrit seeks to provide guidance on ways quantitative methods and data analysis can pursue equitable data use and interpretation under the acknowledgement that numbers, data, their interpretation and their use are not unbiased. It embraces a “conceptual model for the sedimentation of intersecting inequalities” (López et al., 2018, p. 200) to attempt what Zuberi (2008, p. 132-133) calls ‘deracializing statistics’:

Statistical models that present race as a cause are really statements of association between the racial classification and a predictor of explanatory variable across individuals in a population. To treat these models as causal or inferential is a form of racial reasoning... Before the data can be deracialized we must deracialize the social circumstances that created race. Statistical research can go beyond racial reasoning if we dare to apply the methods to the data appropriately.

In application of deracializing “achievement gaps” and considering factors of inequitable access, QuantCrit can serve as a meaningful guiding framework for how to consider instead *how disproportionate outcomes are driven by racism*. In particular, QuantCrit can aid in the transparency of how the use of racial categories has limitations. In Montana, the “Achievement Gap Report” attempts to be as comprehensive as it can by combining the categories of American Indian or Alaskan Native with Multiracial to create a more encompassing category of Native. However, QuantCrit would encourage further articulation that the categories themselves are inherently limiting, even oppressive, as self-identification categories. For research efforts seeking to explore the impact of opportunity factors (e.g. poverty) outside of traditionally used performance metrics in measuring “achievement gaps,” QuantCrit can be a guide for metric selection and articulation of its limitation for school and student level poverty. In Montana it can be challenging to accurately capture neighborhood poverty in rural communities and school-wide

distribution of free lunches sets limitation through use of National School Lunch Program data. Through a QuantCrit framework, criticism of “achievement gaps” calls for the critical analysis how these gaps are cyclically measured, what limitations exist in their measurement, and how adaptation in the collection, analysis, and reporting of disparity between student groups can provide a more accurate data story. In this paper, the inequity of resources are explored, include the student experience factors of poverty and mobility.

### Racialized Poverty Patterns on Academic Achievement

The oppression of school segregation, as segregationist law and practice, has ideological foundations in racial biological inferiority beliefs of the nineteenth century that white people should not interact with people of color (Menchaca, 1997; Valencia, 1997). In the late 1800s, discourse was poignantly racist (Blum, 1978; Valencia, 1997) claiming cultural and intellectual inferiority of people of color justifying inferior treatment. “[R]oots of deficit thinking were inextricably tied to racist discourses that evolved from the early 1600s to the late 1800s. Out of these discourses came beliefs that racial minorities were physically, cogitatively or culturally inferior to whites...[and] was used to justify [their] economic exploitation” (Menchaca, 1997, p. 37). Most racial minorities were denied public education until the early 1900s where then deficit thinking was critical in the promotion of school segregation in the late 1890s and early 1900s. Federal Supreme Court case *Plessy v. Ferguson* (1896) gave states the right to implement school and public space segregation. In addition to biological inferiority, forced segregation was based on a deficit view that students of color were “intellectually inferior, linguistically limited in English, unmotivated, and immoral– all characteristics that would hold back the progress of white students if racial/ethnic mixing in schools was permitted” (Valencia, 1997, p. 4). Naturally,

the practice of segregation led to inferior schooling for colored students with deteriorated physical space, inadequate supplies and curriculum. School segregation is largely responsible for the foundations of racialized and geographically influenced school-level poverty.

Segregation and School-Level Poverty. School conditions directly influence students' academic achievement including teacher quality (McCaffrey et al., 2004; Rivkin, 2000; Writ, 2005), class sizes— in relation to teacher-to-student ratio where smaller class sizes are associated with increased achievement particularly for low-income students (Angrist & Lavy, 1999; Krueger, 1999; Rvkin et al., 2005), and school funding (Jackson, 2020). And, students in high poverty schools where school conditions negatively influence academic achievement are directly impacted by historical and current segregation (Card & Rothstein, 2007; Gamoran & An, 2016; Matheny et al., 2023; Owens, 2018; Reardon et al., 2014; Reardon et al., 2019; Reardon, Weathers, et al., 2019;). Racial/ethnic school segregation is notably stagnant over the most recent 25 years (Johnson, 2019; Reardon & Owens, 2014) where even school segregation is as high today as the 1960s in some places (Orfield & Frankenberg, 2014). While American schools have seen little change in racial segregation, there is substantial growth for socioeconomic school segregation (Duncan & Murnane, 2011; Owens et al., 2016) where socioeconomic segregation between schools is strongly associated with academic and performance disparity (Owens, 2018; Reardon, 2016). The concern in current research of socioeconomic factors' influence on student achievement is that districts with growing socioeconomic segregation will also see widening achievement disparities (Reardon, Weathers, et al., 2019).

The Impact of Poverty on Academic Achievement. Since the 1970s, average standardized test scores in the U.S. have increased, particularly for elementary and middle school students

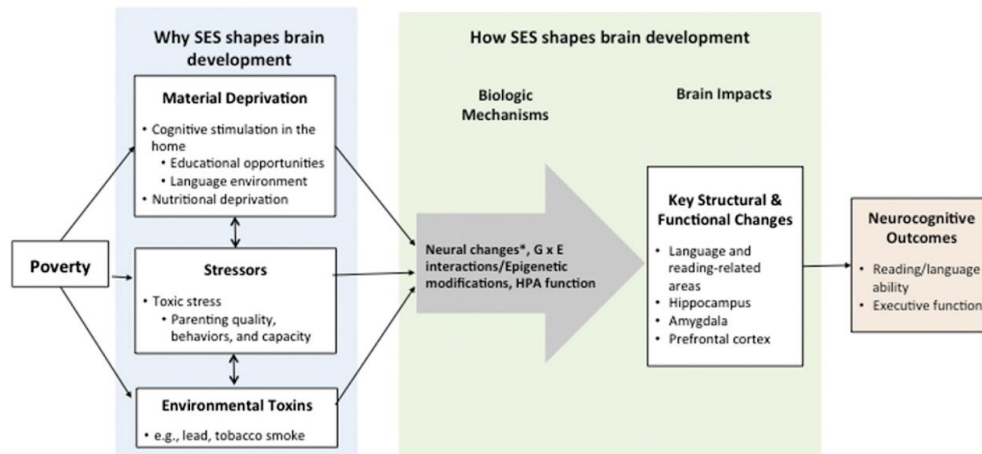
(NCES, 2013; Shakeel & Peterson, 2022). The average fourth grader in 2019 has a math score approximately one standard deviation higher than fourth graders in 1996 (NCES, 2020). The implications of growth perhaps reveal increased opportunities for students today in their homes, neighborhoods and schools (Matheny et al., 2023). However, the academic disparity for students of poverty does not reveal improved and equitable opportunity. The disparity between students receiving free/reduced priced lunch (FRPL) and their non-eligible peers has remained stable across the last several decades (NCES, 2020). Further, the disparity between high-income (90th percentile) and low-income (10th percentile) students has widened in the same span of decades (Hashim et al., 2020; Reardon, 2011; Reardon, 2021). In this way, while on the surface it may seem as though a bookmarked trend of academic growth has bloomed in most recent decades, examining by individual and school level poverty reveals the histories of resource inequity trail to the modern classroom.

Poverty functions, undoubtedly, as a significant factor impacting students' access to their academic experience. One conclusion of The Coleman Report (1966) articulated that family economic status was more prominent in predicting the academic success of a student as compared to funding discrepancies between predominantly white and Black schools as previously believed (Blazer, 2009; Coleman et al., 1966). In the United States, where about 1 in 5 children live in poverty (DeNavas-Walt, 2013; Johnson et al., 2016) better understanding the impact of poverty on the educational attainment of students persists as an area of concern in order to equitably serve the nation's students. Research in the field of education articulates both individual-level poverty and school-level poverty as distinct predictors of academic achievement,

while research in the field of neuroscience reveals perhaps even generational and developmental significant differences for those students raised in high poverty environments.

The Effect of Poverty on Brain Development. Research in the field of neuroscience and brain development considers the impact of poverty on the academic experience of children. Compared to their peers, children in poverty are not only more likely to experience developmental delay and attain lower performance on achievement tests, but a child's SES maintains relationship to their educational attainment, health, and psychological well-being decades later (Ackerman et al., 2004; Brooks-Gunn & Duncan, 1997; Brooks-Gunn & Klebanov, 1994). Brain development in children is impacted by both genetics and environment (Shonkoff & Garner, 2012), and further, the extent of development may vary by SES (Johnson et al., 2016). In this way, behavioral genetics research suggests some genetic variants in children may vary significantly based on the environment of the child (Brody et al., 2013; Chiang et al., 2011; Ellis et al., 2011; Holz et al., 2014; Simons et al., 2011; Turkheimer et al., 2003) where material deprivation and stress are environmental factors of SES in relationship to poverty shaped neurodevelopment (Lipina et al., 2013; Sheridan & McLaughlin, 2014).

Figure 2. Framework Based on Animal Neuroscience Research from Johnson et al. (2016) p. 9

**FIGURE 1**

A framework based on animal neuroscience research. G x E, gene-environment interaction. \*Neural changes = changes in neural plasticity, pruning, synaptic connections, dendritic branching, myelination.

Material deprivation as an environmental factor includes the consideration for cognitive stimulation in the home. For children growing up in poverty, parents may have limited access to provide children cognitive stimulation such as toys, books, educational opportunities (Conger et al., 2010; Hart et al., 1997; Lipina et al., 2013;) and patterns of language. Research suggests that children from low-income homes are exposed to fewer words and less complex patterns of speech (Hart et al., 1997; Kuhl, 2010; Weisleder & Fernald, 2013). Material deprivation also includes nutritional deprivation. Children and infants from low-income homes may experience nutrition deprivation of micronutrients due to factors such as food insecurity (Kant & Graubard, 2012; Magge et al., 2013). Considering stress as another environmental factor, research suggests children growing up in poverty are more likely to experience external stress such as family conflict, separation, household crowding and neighborhood disorder (Evans & English, 2002; Evans et al., 2018). Exposure to excessive stress hormones can impact cognitive development

and mental health of the developing brain. Experiences with poverty, individually and generationally, can impact opportunity and access in cascading effect.

The Effect of Individual-Level Poverty on Academic Achievement. Research in the field of education reveals a student's experience with poverty impacting academic achievement is influenced both by individual as well as school-level poverty concentration. Existing research illuminates a relationship between students' individual socio-economic status and their academic achievement where low-income students have significantly lower test scores than their peers.

Barton and Coley (2009) articulated such a relationship using 2007 National Assessment of Education Progress (NAEP) eighth grade reading and math data. Examining the effect of poverty using National School Lunch Program (NSPL) data, low-income students (students receiving free or reduced priced lunch (FRPL)) in this study scored 25 points lower in reading and 28 points lower in math compared to their peers. Also using NAEP data, Berliner (2009) found individual poverty maintained a relationship with lower performance scores regardless of school poverty. Rowan et al. (2004) reported significant differences in achievement between students based on family income on the U.S. Department of Education's Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K). Students in the lowest fifth of family income scored at the 30th percentile while students in the middle fifth and the top fifth scored in the 45th and 70th percentiles respectively. Also using the ECLS-K, Lee and Burkam (2002) explored a representative sample of over 16,000 children ages five and six finding that the children from the lowest income homes were 60 percent lower in Math and 56 percent lower in Reading scores compared to the children in the highest income homes. Gottlieb (2002) also reported significant differences in achievement by family income using the Colorado Student

Assessment Program (CSAP) and Iowa Test of Basic Skills (ITBS) reading scores of 13,245 students across 89 Denver elementary schools. In this study, 85 percent of the difference between test scores was explained by socioeconomic status.

The patterns explored between individual socio-economic status and academic achievement extend prior to the last two decades. Using family income data from the Panel Study of Income Dynamics, which is a longitudinal survey of U.S. households, Levy and Duncan (2000) revealed that for the first 15 years of a child's life— particularly during the timeframe from birth to age 4— providing a family with a 2.7 fold increase in their income annually increased the length of the child's educational career by about three-quarters of a year. Smith, Brooks-Gunn, and Klebanov (1997) used data from the Children of the National Longitudinal Survey of Youth and the Infant Health and Development program to compare cognitive development between families above and below the poverty threshold. This study revealed children from the lowest income homes scored 6 to 13 points lower on various assessments where it is noted could be the score difference placing students in a Special Education classroom. The study also examined children in homes closer but still below the poverty line and found consistent lower achievement compared to peers above the poverty line.

The Effect of School-Level Poverty on Academic Achievement. Existing research also reveals a negative relationship whereas the poverty level of a school rises, the achievement levels of its students fall. Berliner (2009) reported using data from the 2007 Trends in International Mathematics and Science Study (TIMSS) that the math scores of fourth grade students decreased as the percent of disadvantaged students (based on FRPL status) within a school increased. Similarly, Berliner (2009) reported low and middle income fourth grade students' math test

scores on the 2005 NAEP decreased as a school's poverty concentration increased. Kahlenberg (2004) examined 2000 NAEP data found low-income students who attend middle class schools had higher average math scores than middle income students who attend high poverty schools. In this study, a middle-class school is defined as 26 to 50 percent of students eligible for free or reduced price lunch where a high poverty school is 76 to 100 percent eligibility. Andrews and colleagues (2003) examined a variety of Louisiana assessment scores across grades kindergarten through eighth grade and found that as concentrations of school poverty increased, achievement scores decreased. Rusk (2002) examined Wisconsin public school data and found that middle class students test scores declined as the percentage of low-income students increased within a school. Further, that when the percentage of low-income students exceeded 60 percent in a school building that test scores decreased significantly across low-, middle-, and high-income students. And in a study commissioned The Piton Foundation, Gottlieb (2002) reported that low-income students had significantly higher reading test scores on the Colorado Student Assessment Program (CSAP) when they attended a school with 50 percent or less low-income student population as compared to low-income students attending a school with a high concentration of poverty.

School poverty seems to predict lower rates of academic achievement in historical studies as well. Tschinkel (1999) analyzed 1997 writing, reading and math scores from seven districts in Florida and found that 60 to 80 percent of the differences in performance were predicted by a school's percentage of students eligible for free and reduced lunch. In this study Tschinkel controlled for a wide variety of factors including student mobility, frequency of long absences, number of gifted, limited English proficient, and disabled students, teachers' average years of

experience, the number of teachers holding master's degrees, the number of students enrolled in the school, the number of teachers and staff working at the school, average class size, and per-student costs. Using data from the 1988 National Education Longitudinal Study, Anderson and colleagues (1992) revealed that the highest poverty schools (based on free or reduced price meal eligibility) experienced the lowest scores across all four subject area tests. In addition, the greatest declines in average test scores were found in schools with the highest concentration of low-income students. Rumberger and Palardy (2002) also used the 1988 National Education Longitudinal Study to estimate achievement growth of students between eighth and twelfth grade in all four subject areas across 913 high schools. Controlling for individual students' race, income level and prior academic achievement, the study found high schools with a higher income student population correlated with higher test scores as compared to students who attended schools with higher poverty concentrations, indicating the impact of school poverty alone on academic achievement.

The Impact of Poverty on Academic Achievement in Montana. The factor of poverty is one pivotal issue contributing to inequitable access of Native students, evident in both National and state-level data. According to the 2021 Census, 7.4 percent of American Indian or Alaskan Native (AIAN) children under age 18 and 12.4 percent of the total AIAN population live in poverty (Around Him & Gordon, 2022). Nationally, about one quarter of AIAN students attend high density schools, and about one quarter of students attend rural schools (NIEA, 2023). The National Indian Education Study (Rampey et al., 2021) of 2019 reports on Native student school location by identifying as low density or high-density schools, where about 30 percent of students attend high density schools, and 60 percent at low density schools forming a

representative sample of the nation (Rampey et al., 2021). Students in Montana who attend high density schools also attend rurally defined schools (GEMS, 2023c).

Since about half of Native students in the U.S. attend rural districts (NCES, 2008), examining rural school trends more generally provides insight. According to the most recent *Why Rural Matters* report (Showalter et al., 2023), one in five students in the U.S. attend a rural school. The communities surrounding rural districts across the nation have an average household income of 2.91 times the poverty line, or 291%. Montana ranked 19<sup>th</sup> or 2.67 (267%)<sup>th</sup> in the nation for poverty level in rural school communities. Ranking 17<sup>th</sup> in the nation, Montana has about 10.3 percent of rural households with school-aged children who changed residences within the previous 12 months (household mobility). Montana’s “student mobility is high with one in ten students changing residences per year” (Showalter et al., 2023, p. 118). Number two in the nation, Montana has about 74 percent rural schools, and number one in the nation, Montana has about 75 percent rural districts. Approximately 49,168 students (Showalter et al., 2023) attend a rural school in Montana and about 12,500 of Native students (about 60 percent) attend a high-density school (GEMS, 2023c). While slightly dated, the National Center for Education Statistics (NCES) provides about 33 percent of people who identify as AIAN ages 5 through 17 in the U.S. live in poverty (NCES, 2008). Considering Montana has the second highest percentage of rural schools in the nation (Showalter et al., 2023) where the majority of reservation schools in Montana are rural and experience higher rates of poverty (Provasnik et al., 2007), the percent of rural school-aged children in poverty at about 11 percent (Showalter et al., 2023) does not seem to accurately capture experiences of Native student poverty and impact for the state.

*Why Rural Matters* also investigates a variety of relationships between different indicators using bivariate correlation analysis. The strongest correlations which presented were between poverty measures ( $r = .70$ ) as well as between rural diversity and rural student mobility ( $r = -.34$ ): “In other words, states with more rural students changing residences were also more likely to have more racial diversity” (p.31). Interestingly, the most recent report found rural high school students indicate higher graduation rates compared to their non-native peers. Across the United States rural students (89.8 percent) graduate 2.6 percentage points higher than non-rural students (87.2 percent). Montana displays a similar trend with an advantage of 3.1 percent points higher graduation rate for Montana rural students. Despite the improvements of rural academic completion in Montana, it appears students still face the impact of opportunity factors where over 11 percent of Montana rural school-aged children experience poverty and over 10 percent experience household mobility (Showalter, 2023).

The relationship between rural poverty and Montana’s Native schools and student population warrants further research. Existing insights indicate a spatial relationship that can be represented using the U.S. Census Bureau’s Small Area Income and Poverty Estimates (SAIPE). Figure 3 and Table 1 provide SAIPE estimates for Montana school districts with a 50 percent or higher AIAN student population ( $N = 40$ ), focusing on school-aged children (ages 5-17) in 2021. The areas outlined in red align with Montana’s reservation territories, where these 40 school districts have an average poverty ratio of 26.88 (SAIPE, 2023). These statistics underscore the need for focused research and policies to address the unique challenges of Native students in Montana's high-poverty, rural districts. National averages often hide the severe effects of poverty and mobility within Native communities, but Montana-specific data show these issues are

intensified in reservation-based rural schools. Educational support strategies in Montana must consider the combined impact of economic hardship and mobility among Native students.

Figure 3. Map of Montana School Districts with 50 Percent or Higher American Indian Student Population, Ages 5-17 in Families in Poverty 2021

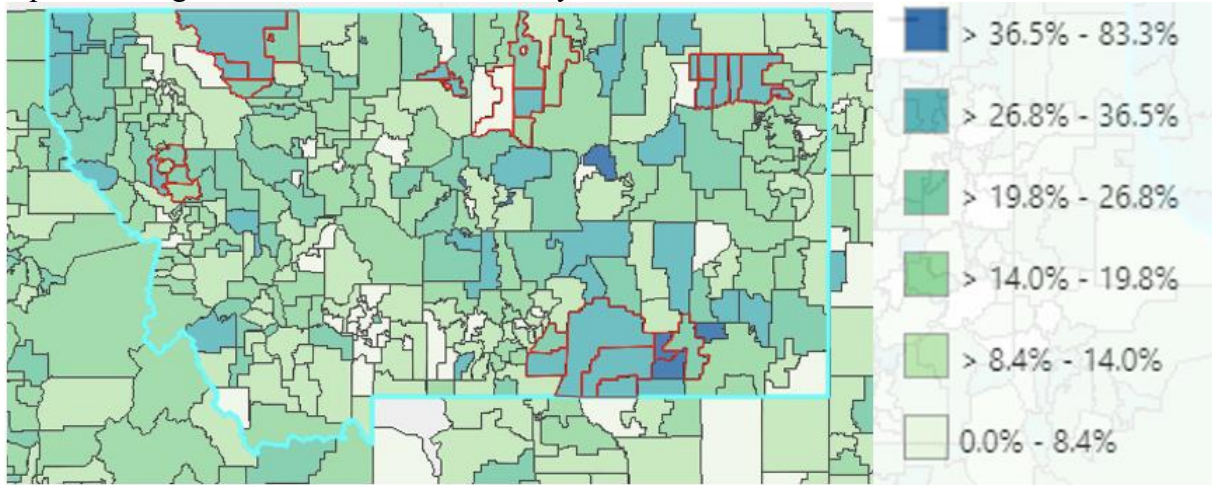


Table 1. Table of Top 20 Montana School Districts with 50 Percent or Higher American Indian Student Population, Ages 5-17 in Families in Poverty 2021 by Poverty Ratio

Year	ID	Name	Grades	Total Population	Relevant Ages 5 to 17	Relevant Ages 5 to 17 in Families in Poverty	Relevant Ages 5 to 17 Poverty Ratio
2021	3016050	Lame Deer Elementary School District	PK-08	2,063	436	161	36.9
2021	3005040	Brockton High School District	09-12	632	68	25	36.8
2021	3009030	Dixon Elementary School District	PK-08	485	53	19	35.8
2021	3021240	Poplar Elementary School District	PK-08	3,469	656	230	35.1
2021	3028800	Wyola Elementary School District	PK-08	435	74	26	35.1
2021	3021270	Poplar High School District	09-12	3,469	317	111	35.0
2021	3005010	Brockton Elementary School District	PK-08	632	114	38	33.3
2021	3009510	East Glacier Park Elementary School District	PK-08	578	78	26	33.3
2021	3021720	Pryor Elementary School District	PK-08	718	134	44	32.8
2021	3017010	Lodge Grass Elementary School District	PK-08	2,290	435	142	32.6
2021	3011670	Frontier Elementary School District	PK-08	368	51	16	31.4
2021	3004440	Box Elder Elementary School District	PK-08	517	99	30	30.3
2021	3011460	Frazer High School District	09-12	746	63	19	30.2
2021	3005140	Browning Elementary School District	PK-08	8,589	1,510	452	29.9
2021	3000095	Lame Deer High School District	09-12	4,882	402	119	29.6
2021	3028590	Wolf Point Elementary School District	PK-08	4,230	722	211	29.2
2021	3013310	Hardin Elementary School District	PK-08	9,445	1,624	472	29.1
2021	3022750	Rocky Boy Elementary School District	PK-08	3,303	650	189	29.1
2021	3011420	Frazer Elementary School District	PK-08	542	101	29	28.7
2021	3013660	Hays-Lodge Pole K-12 Schools	PK-12	1,553	418	116	27.8
2021	3018960	Morin Elementary School District	PK-08	374	60	16	26.7
2021	3017040	Lodge Grass High School District	09-12	2,149	165	42	25.5

Examining the patterns of socioeconomic status and academic achievement in Montana reveals significant disparities in proficiency levels across student demographics, particularly among those impacted by poverty. Students from lower socioeconomic backgrounds, as indicated by participation in the Free and Reduced Price Lunch (FRPL) program, are substantially less likely to attain proficient scores on Montana's standardized assessments. During the 2022-2023 school year, 48.56 percent of students not participating in FRPL achieved proficient scores, while only 25.23 percent of students receiving FRPL met proficiency benchmarks. The disparity widens further for Native students receiving FRPL, with only 14.17 percent achieving proficiency (see Table 2). Although FRPL data only provide a proxy measure of socioeconomic status, the pronounced relationships between poverty, race, and academic achievement signal the need for deeper exploration and understanding of these dynamics.

Research consistently underscores the connection between a school's socioeconomic context and students' learning opportunities (Mickelson & Bottia, 2010; Mickelson, 2018; Kahlenberg, 2013; Reardon et al., 2019). This relationship is particularly evident in Montana, where many Native students face poverty as a significant barrier to educational success. However, these geographies of poverty should not be seen merely as a matter of spatial inequity; rather, educational inequity exists at the intersection of social, spatial, and historical dimensions (Morrison et al., 2017, p. 6). For Native students, the overlapping contexts of school geography, poverty, and race intersect with historical issues of educational and land reform, creating complex layers of disadvantage. Despite the persistent and impactful nature of poverty on Native students' educational experiences, such dimensions are often overlooked in gap reporting. This lack of attention to poverty as a fundamental factor in educational inequity limits our

understanding of the barriers many Native students face and emphasizes the importance of including socioeconomic factors in assessments of educational achievement and equity.

Table 2. Percent of Students Attaining Proficient Scores on the Suit of Montana Standardized Assessments during the 2022-2023 School Year for All Students and Native Students

<b>ACT - Grade 11</b>						
	All Students			Native Students		
	ELA	Math	Science	ELA	Math	Science
Receiving Free or Reduced Meals	35.80	15.90	16.90	22.5	8.00	9.00
Not Eligible or Not Participating	61.70	37.60	36.60	50.60	28.60	26.20
<b>Smarter Balanced - Grades 3-8</b>						
	All Students			Native Students		
	ELA	Math	Science	ELA	Math	Science
Receiving Free or Reduced Meals	30.89	24.33	NA	17.13	12.50	NA
Not Eligible or Not Participating	56.13	47.84	NA	46.17	37.85	NA
<b>Montana Science Assessment - Grades 5 &amp; 8</b>						
	All Students			Native Students		
	ELA	Math	Science	ELA	Math	Science
Receiving Free or Reduced Meals	NA	NA	27.56	NA	NA	15.89
Not Eligible or Not Participating	NA	NA	51.53	NA	NA	40.12

Racialized Mobility Patterns on Academic Achievement

Resource inequity is framed by histories of school segregation as racialized and geographically influences to school-level and individual-level poverty. Another factor which requires geographic context in defining inequity of resource and the impact on academic achievement is student mobility. As an outcome of school choice policy from integration efforts, student mobility presents as an unexpected student experience factor also from the platform of

school segregation and geographically influenced patterns. In many ways, student mobility is inextricably linked to individual and school-level poverty where students with high mobility rates also tend to come from high poverty and minority neighborhoods. The schools that students attend, the neighborhoods in which they reside, as well as the schools and neighborhoods they move to paint a deeper understanding of resource inequity within the frame cast by poverty.

Brown vs. Board of Education (1954, 1955). In 1896, the Supreme Court's decision in *Plessy vs. Ferguson* established legal grounds for segregated public facilities and services, including public schools. In 1954, the Supreme Court reversed the decision in *Brown vs. Board of Education* where it was held that public school segregation was unconstitutional. While *Brown* addressed the broad issue of public-school segregation, it inadequately articulated a remedy for those affected by public school segregation. The Supreme Court addressed this in a separate opinion, *Brown vs. Board of Education (1955)* – also referred as *Brown II*– providing guidance on schools' responsibilities for the creation and implementation of desegregation plans. One outcome of the *Brown* decisions was the offering of school choice as part of desegregation policy at the local level (La Morte, 2012). In reality, schooling placement and choice is largely determined by residential and geographic boundaries.

Student mobility became a product of the decisions in *Brown* as districts nationwide offered school choice as part of their *Brown II* desegregation plans (U.S. Commission of Civil Rights, 1973). While desegregation plans offering school choice theoretically allowed students to attend schools more reflective of their preferences and geographic locations, many students chose to remain due to realities of racism and violence (Equal Justice Initiative, 2017). Student mobility, from its inception then, reflects complex social and economic driving factors.

Studying student mobility patterns, while perhaps an unexpected avenue out of *Brown vs. Board of Education*, serves as an important means for understanding the integration of schools and improved student outcomes (Welsh, 2019). Student mobility is driven by a complexity of social and economic factors (Kerbow, 1996; Kerbow et al., 2003; Pribesh & Downey, 1999; Rumberger & Larson, 1998; Rumberger et al., 1999; Welsh, 2017, 2019). High mobility rates reveal inequitable access in education (Ingersoll et al., 1989), particularly for minority and low-income students (Hanusheck et al., 2004; Rumberger, 2015; Schwartz, et al., 2009; Xu et al., 2009). Additionally, lower socio-economic status correlates with higher mobility rates and lower academic achievement (South et al., 2007). While school choice as an outcome of *Brown* desegregation plans ideally would improve student access in academic environments, student mobility is frequently damaging and disproportionately impacts groups of students.

The Impact of Mobility on Academic Achievement. As a widespread phenomenon in the U.S. (Welsh, 2019; 2017; Rumberger, 2015; United States Government Accountability Office, 2010), student mobility— and more specifically non-structural mobility or when students move between schools on their own, separate of structural changes such as a building move from middle to high school— is complex and an outcome of intersecting social and economic factors (Welsh, 2019) driven by both the academic and non-academic scenarios of schools and neighborhoods (Rumberger, 2002). Such factors may include residential mobility (movement between houses), family scenario or circumstances (both positive and negative), or schooling preference (Kerbow, 1996; Kerbow et al., 2003; Pribesh & Downey, 1999; Rumberger et al., 1999; Rumberger & Larson, 1998; Swanson & Schneider, 1999; Welsh, 2019; 2017).

The literature dedicated to understanding student non-structural mobility is almost exclusively focused on illuminating patterns among urban school districts as policy implications of segregated and integrated school environments are most concentrated to urban ecosystems. Welsh (2017) reveals that mobility rates are higher in urban school districts compared to suburban and rural districts. Of student mobility in urban school districts, low-income and minority students experience higher mobility rates and face negative impacts on academic success due to their mobility (Hanushek et al., 2004; Schwartz et al., 2009; Xu et al., 2009). The higher mobility rates of low-income and minority students in urban school districts may in part explain the disparity in “achievement gap” outcomes (Hanushek et al., 2004).

Across the nation, segregation in schools continues to rise (Ayscue et al., 2016) despite policy and efforts to offer student choice and school integration. The phenomenon of continued school segregation has resulted in minority students more likely to attend inferior schools (Orfield & Yun, 1999). The presence of segregated schools has doubled since 1988 (Stancil, 2018) and schools with only 0-10% white students has tripled (Orfield et al., 2016). In Montana, the segregation of schools by race functions under a different phenomenon where the majority of school segregation separates Native students from their non-Native peers. Using 2022-2023 school enrollment counts, the majority of students in the K-12 system identify as white (77.4 percent) and the second largest racial category is students who identify as Native (15.2 percent), where Native comprises those students who identify as American Indian/Alaskan Native or Multiracial (GEMS, 2023b). Within the Native student population, almost 40 percent attend a school where 75-100 percent of the school student population is also Native, and approximately 37 percent of Native students attend a school where 0-24 percent of the school student

population is also Native (GEMS, 2023c). In addition, understanding school segregation in the rural state of Montana must take into account the geographic and historically informed presence of reservations and reservation schools. While Indigenous peoples were segregated onto reservation lands as part of early colonization and land reform policy, today reservation schools are most sensitive to cultural norms and curricular relevance for its predominantly Indigenous students. While literature of urban ecosystems points to the end of court order desegregation plans (Liebowitz, 2018; Orfield et al., 2016; Stancil, 2018), the expansion of segregated charter schools (Frankenberg et al., 2010; Walker, 2018), and residential segregation (Orfield et al., 2016) as catalysts for continued school segregation, Montana's lands, communities, and histories undoubtedly present unique geospatial, social, and cultural factors influencing continued segregation.

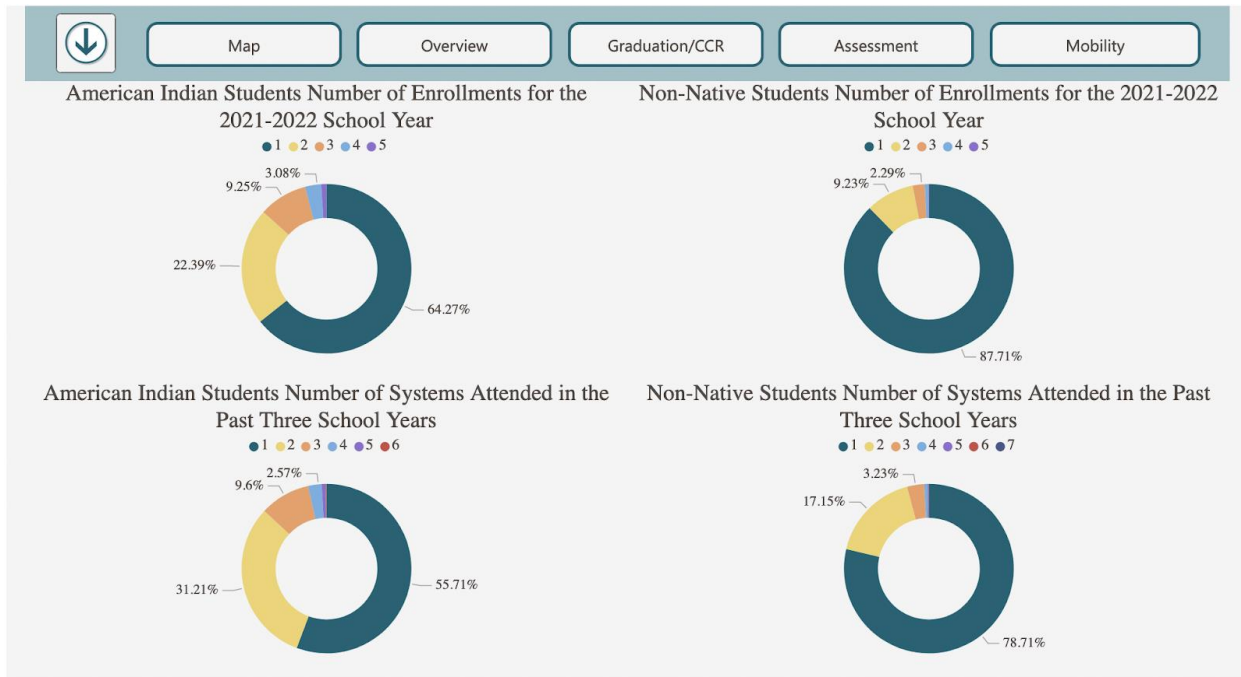
Despite the limited understanding of rural ecosystem mobility patterns among K-12 students, the motivation for Welsh's research of urban mobility rings true for Montana rural mobility patterns: "Examining the relationship between the patterns of student mobility, segregation and neighborhood characteristics provide a window into educational inequality and allow for a richer understanding of segregation and student mobility as a *process* rather than as events" (Welsh, 2019, p. 495 [emphasis added]). The processes of Montana student mobility cannot be understood without the collection of voices describing the catalysts and experiences of mobility, particularly for Indigenous students. However, as little is known about student mobility patterns in Montana, research should first seek to illuminate what patterns exist knowing rich understanding must rely on the collection of stories and lived experiences. Without the collection of these qualitative understandings, suggestions for informing policy will be ill-equipped.

The existing recommendations in literature exploring urban student mobility lean into integration efforts based on literature that reveals a racially and socioeconomically integrated environment is best for all children's learning (Hilbert, 2018; Learned-Millner, 2017; Potter et al., 2016; Siegel-Hewley, 2012; Wells & Crain, 1994; Wells et al., 2016) where such environments also produce increased test scores, graduation rates, college attendance, and adult income (Chetty et al., 2016; Eaton, 2010a; 2010b; Kainz & Pan, 2014; Massey & Fischer, 2006; Mickelson & Bottia, 2010; Stearns, 2010; Swanson, 2004; Tegeler et al., 2010; Wells et al., 2016). However, more needs to be understood about the experiences of Native students to integrated school environments. For example, a recent study in the Montana context revealed student perceptions of feeling alienated, isolated, and removed from their cultural norms when they moved away from an on-reservation school (Clausen et al., 2020). It is important to note that integration requires student mobility, and cultural isolation may explain some of these patterns of student choice (Welsh, 2019).

Amidst these important nuances, the relationship between neighborhoods and schools is imperative to understanding educational inequity. These relationships are not surprising: the demographic makeup of a neighborhood is represented in the demographic composition of its schools (Burdick-Will & Logan, 2017; Owens, 2010). Considering educational outcome measures, low-income and minority families tend to live in disadvantaged neighborhoods (Burdick-Will et al., 2011) and students in disadvantaged neighborhoods tend to have higher mobility (Cordes et al., 2015). In addition, as there is a relationship between student absences and student mobility (Welsh 2018), it is relevant that neighborhoods with high poverty predict more student absences (Gottfried, 2014). The segregation of resources is also a prominent

argument for integration efforts as the distribution of school resources is typically tied to local revenues, and as previously noted, low-income and minority students are more likely to attend segregated schools from low-income, high minority communities. Resource segregation in schools demonstrates structural inequity in U.S. society (Wells, 2014; Welch, 2019), a reality poignant in on-reservation and predominantly Native schools in Montana.

The Impact of Mobility on Academic Achievement in Montana. As geographic context functions as a large determining factor in schooling placement, Native students face unique scenarios of school choice and mobility. Almost half of Native students in the U.S. attend rural districts (NCES, 2008), many of which are located geographically on reservation land. While existing research identifies that mobility rates are higher in urban than suburban and rural districts (Welsh, 2017), little research examines the impact of student mobility in rural school environments specifically (Paik & Philips, 2002). Despite the limitation of insight to rural student mobility, and even more for Native rural student mobility, Montana may serve as a pivotal location to understand how school choice and student mobility impact inequitable access in education. Montana has the second highest percentage of rural schools in the nation (Showalter et al., 2023) where the majority of reservation schools in Montana are rural and experience higher rates of poverty (Provasnik et al., 2007).

Figure 4. Mobility Page of the American Indian Student Achievement Dashboard<sup>1</sup>

Mobility data in Montana highlights Native students have higher mobility rates and lower achievement rates compared to their non-Native peers. While only about 12 percent of non-Native students in Montana had two or more school enrollments during the 2021-2022 school year, over 35 percent of Native students did. Additionally, while only about 21 percent of non-Native students, over 44 percent of Native students had two or more systems attended over three consecutive years (GEMS, 2023c). Native student mobility in Montana inspires inquiry of factors surrounding school choice where the social and economic geographic power structures, historically enabled through colonization and assimilation inspired policies, fuel the complexity.

The imbalance of students from the most privileged backgrounds continuing to dominate educational opportunities, persists as an enduring social problem. Examining specifically the

<sup>1</sup> Image from the AISA Dashboard of the public facing GEMS website ([gems.opi.mt.gov](https://gems.opi.mt.gov)) retrieved 2.08.2024

impact of poverty and mobility—both at the individual and school levels—on academic achievement reveals factors informed by a complexity of experiential scenarios and issues. These factors are irrevocably linked to histories and outcomes of school location, segregation, and integration, further evolving then into factors requiring geographic context to grapple with the impact on student success measures and experiences. In Montana, the prevalence and patterns of poverty and mobility for Native students is likewise woven within the histories, patterns and trajectories of resource inequity.

### Chapter Summary

Commonly referred to as “achievement gaps,” or the “difference in academic outcomes between historically advantaged and disadvantaged groups” (Valant & Newark, 2016, p. 331), trends of lower academic success among racial groups are a major practice, policy and research concern (Carey, 2014; Shukla et al., 2021). The gap in academic achievement between students of color and white students cannot be summed by performance scores alone. Rather, the perception is left unacknowledged by the abundance of inequalities which impact student performance and the disparity between students (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010). As part of the movement of NCLB (2002), and roots back to the Coleman Report (1966), the collection and reporting of academic outcomes of students and schools has spurred decades of generating “achievement gap” data and reports. In Montana, the— *American Indian Student Achievement Report* often referred to as the “Achievement Gap Report”— has been generated on a biennial basis.

To critically examine “achievement gaps”—including the discourse in Montana between Native and non-Native students— expanding study needs to articulate the frame of inequity of

space and inequity of resources around opportunity factors impacting academic success. Inequity of space aligns the histories of land and school reform for Indigenous people to the ways schools reveal how power is structurally inscribed and reinforced. By using a framework of Critical Race Spatial Analysis (CRSA) underneath the umbrella of Critical Race Theory (CRT), aligning “achievement gaps” to unjust geographies “makes visible the fingerprints of white supremacy in shaping every urban and rural neighborhood” (hooks, 1990, p. 14). Inequity of resource weaves the abundance of experiential factors impacting educational inequity and academic success, namely poverty and mobility within the confines of this paper. By using a framework of Critical Quantitative (QuantCrit), analysis of “achievement gaps” considers instead how disproportionate outcomes are driven by racism rather than by race, contributing to *deracializing statistics* (Zuberi, 2008).

The two experiential factors utilized in this paper to better understand Native to non-Native student disparity in Montana are poverty and mobility. Histories and current realities of school segregation influence the impact of poverty (Card & Rothstein, 2007; Gamoran & An, 2016; Matheny et al., 2023; Owens, 2018; Reardon et al., 2014; Reardon et al., 2019; Reardon, Weathers, et al., 2019) and mobility (Welsh, 2019) on student experience and opportunity within school spaces. School conditions directly influence students’ academic achievement (McCaffrey et al., 2004; Rivkin, 2000; Writ, 2005) particularly for low-income students (Angrist & Lavy, 1999; Krueger, 1999; Rvkin et al., 2005). The concern in current research of socioeconomic factors’ influence on student achievement is that districts with growing socioeconomic segregation will also see widening achievement disparities (Reardon, Weathers, et al., 2019). Student mobility is complex and an outcome of intersecting social and economic factors (Welsh,

2019) driven by both the academic and non-academic scenarios of schools and neighborhoods (Rumberger, 2002). Low-income and minority students experience higher mobility rates and face negative impacts on academic success due to their mobility (Schwartz et al., 2009; Xu et al., 2009; Hanushek et al., 2004). The higher mobility rates of low-income and minority students may in part explain the disparity in “achievement gap” outcomes (Hanushek et al., 2004), however there is need to better understand the experiences of poverty and mobility for rural and Native students.

Both poverty and mobility are geospatially defined and a result of structural and institutionalized histories of power and place. To understand the powerplay impact on student academic success, poverty and mobility must be approached as socially and spatially understood fields. While maps cannot speak for themselves, they spatially illuminate how geographies both contribute and resist inequity for students. In particular for Montana Native students, historically produced reservation lines simultaneously define how opportunity factors such as neighborhood and school-level poverty contribute to inequity while *also* serving as harbors of culture, relationships and self-identity for Native students. Spatially exploring opportunity factors’ impact such as student mobility and poverty on academic success can pivot from deficit perspectives regarding “achievement gaps” (Shukla et al., 2021, Quinn, 2020) to instead acknowledge how these factors spatially inform spaces of school locations.

## CHAPTER THREE

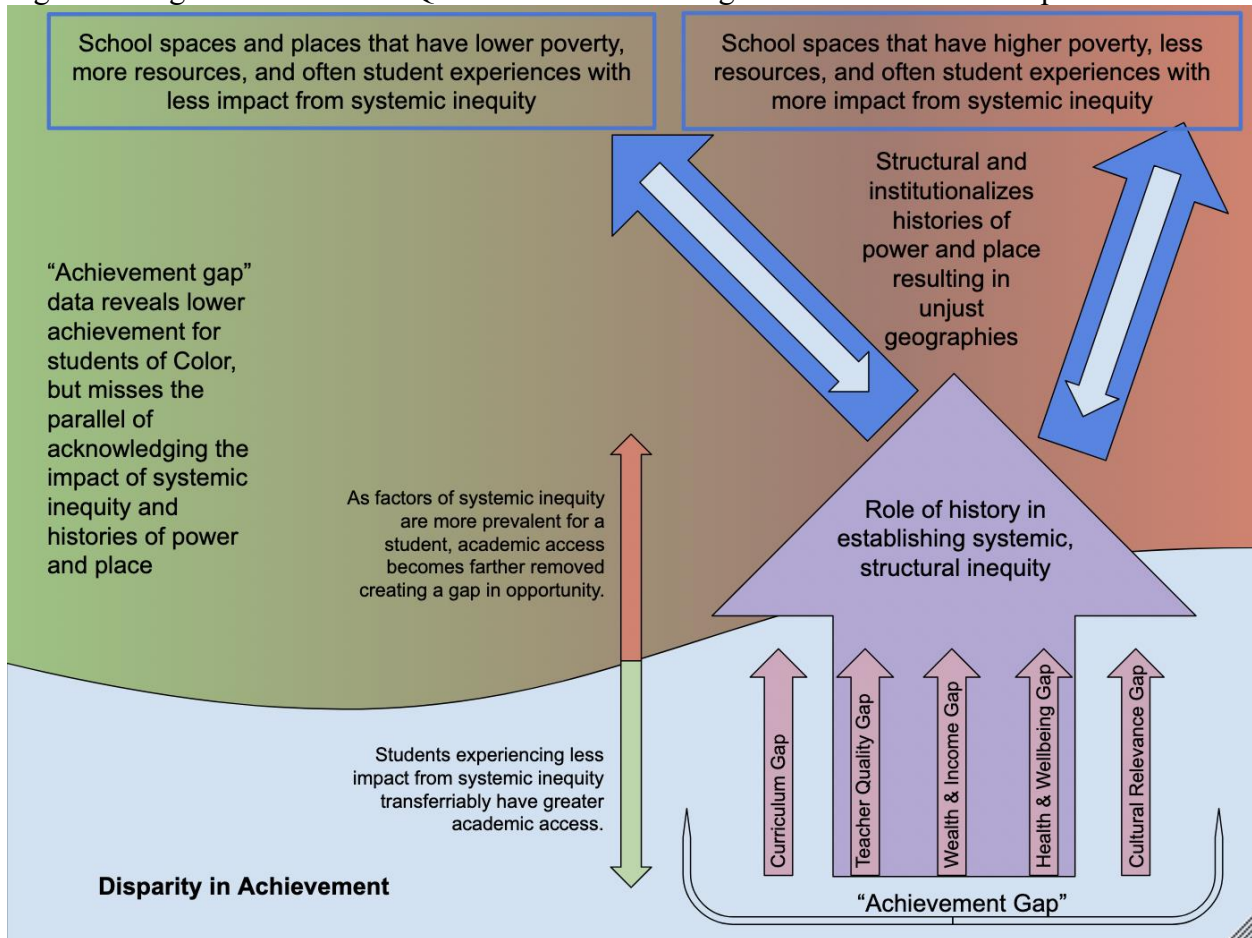
## METHODOLOGY

The current Montana “achievement gap” literature expects only to find a race gap explaining differences in outcomes. QuantCrit aligned with intersectional methodology transforms the question to “how can we examine unique constellations of race, gender, class social location as categories of experience in a given sociohistorical and political economic context?” (López et al., 2018, p. 181). The goal is to reveal inequalities by social locations, rather than strictly efforts focused on race, to “deracialize statistics” (Zuberi, 2001) and illuminate gaps “making the invisible visible” (López et al., 2018), revealing student inequalities that conventionally remain invisible. Or rather, that when examining through social locations, the “achievement gaps” that remain unseen in conventional models and reporting are exposed. By layering students’ mobility and poverty with their social context, a more thorough data story may ensue, ultimately informing the decision-making processes. While other student opportunity factors are needed in developing a robust understanding, the opportunity factors illuminated in this study with students’ social context serves as a major first step in articulating the data story of educational inequity for “achievement gaps” in Montana.

In particular, poverty and students’ mobility function as spatially informed opportunity factors, as both are the result of structural and institutionalized histories of power and place, further aligning CRSA methodology to this study. The utilization of social locations “make[s] the invisible visible” (López et al., 2018) and aligning “achievement gaps” to unjust geographies “makes visible the fingerprints of white supremacy in shaping every... neighborhood” (hooks, 1990, p. 14). The complexity of opportunity and inequity in understanding academic disparity is

great, far greater than the confines of this paper. Instead, this study examines just two spatially informed factors in disrupting Montana Native binary “achievement gap” discourse by inserting into CRT quantitative methodologies of QuantCrit and CRSA. This study does little to resist assumed negativity around unjust geographies. Continued Montana specific research should seek to consider the strengths and cultural harbors that are particularly held in high Native density schools and communities. Further, research should look to collect perspectives on mobility patterns—particularly of Native students—informed by cultural norms, kinship patterns, and stories of relationship (see Chapter 5).

Figure 5. Alignment of Critical Quantitative Methodologies to “Achievement Gap” Norms



Using a dataset generated from the Montana Office of Public Instruction’s Statewide Longitudinal Data System warehouse, the research questions are explored through Montana grade 11 students in the 2018 fiscal year with ACT composite scores, as well as, a completion measure and unique system mobility for these students across the four years 2016-2019. In this way, the sample of the 2019 graduating cohort includes all students and some data spanning all four years of high school. Therefore, the sample can be considered a census of the 2019 cohort. The research questions addressed in this study focus on student-level and school-level factors’ impact on academic achievement and academic completion. In this way, this study seeks to better understand the commonly defined and accepted “achievement gap” in Montana. Existing policy, literature and reporting in Montana particularly describe a disparity in academic success between Native and non-Native students. However, these efforts excite little in exploring opportunity factors which may explain the cyclical pattern of disparity. While the opportunity factors informing access and success in the educational arena are complex in Montana, this study explores poverty and student mobility patterns as two factors which may reveal better understandings of academic inequity, not just for Native students, but all students in the state.

### Research Design & Rationale

This investigation is a nonexperimental research design that involved analysis of longitudinal student-level and school-level data following a single cohort of Montana high school students. The research questions seek to understand the relationships and impact of student experience and poverty on academic success—defined as academic achievement (ACT composite score) and completion (graduation/dropout end status):

1. Are there observable differences by academic achievement based on students' social location orientation (gender, race, class)?
2. Are there observable differences by academic completion based on students' social location orientation (gender, race, class)?
3. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic achievement?
4. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic completion?

Academic achievement and completion are the two dependent variables in this study to align to existing “achievement gap” reporting in Montana. The biennial *American Indian Student Achievement Report* (OPI, 2018; 2020a; 2022) compares academic achievement and completion between Native and non-Native students. Academic achievement is represented as student proficiency on state required standardized assessments: Smarter Balance Assessment (SBAC) grades 3-8 and ACT (grade 11). Academic completion in biennial reporting is represented as graduation and dropout measures by high school cohorts. While this study focuses on only high school students, the dependent variables mirror the biennial reporting where academic achievement is represented as grade 11 ACT composite scores in the 2018 fiscal year and academic completion is represented as grade 12 graduation and dropout measures in the 2019 fiscal year. The choice of dependent variables aligns this study to existing “achievement gap” reporting so findings may converse with existing “achievement gap” policy.

The independent factors of poverty and mobility stressed in this study focus on illuminating where current “achievement gap” reporting is inadequate. These independent factors, or opportunity factors, reveal aspects of students’ academic experience which may better inform disparity between achievement and completion. Focusing first on student-level relationships to achievement and completion, this study reveals patterns on the outcomes by students’ social locations, or the intersections of race, gender and class. Based on the work of López et al. (2018) these social locations are in effort to “deracialize statistics” (Zuberi, 2001) and better understand academic disparity and inequity across student intersectionality rather than on the existing binary between Native and non-Native students only.

School-level poverty is explored as an opportunity factor in this study using the Spatially Interpolated Demographic Estimate (SIDE) ratios from a project of the National Center for Education Statistics. SIDE was developed using data from the American Community Survey and takes a geospatial approach to assigning income to poverty ratios (IPR) for a school community based on a point estimate (physical address). A SIDE measure from the 2019 fiscal year was utilized for each school within the dataset. While student-level poverty is confined to Free and Reduced Lunch (FRPL) data as a proxy measure for socioeconomic status, the school-level measures seek to represent neighborhood poverty as more targeted explanation of students’ experience with poverty. Lastly, student mobility patterns are captured as a total count of unique system enrollments throughout the four high school years relative to the 2019 graduating cohort. In this study, mobility is measured across the academic experience in alignment with practice in existing literature (Engec, 2006; Rumberger & Larson, 1998; Swanson & Schneider, 1999). Understanding frequency of school mobility may lead to insight of opportunity impacts on

academic success. However, consideration for the nuance of student mobility, particularly among Indigenous families and kinship structures, is not adequately captured in this dataset.

This study appropriately utilizes robust linear and logistic multilevel modeling regression to explore the relationships between dependent and independent variables. In this way, robust linear MLM regression is used for the continuous outcome of academic achievement (ACT composite score), and robust logistic MLM regression is used for the categorical outcome of academic completion (graduation/dropout). By first exploring relationships of social locations to the outcome variables, this study seeks to utilize intersectionality within quantitative methods (Crenshaw, 1991; Fine, 1991; Hancock, 2013; LaVeist, 1994; McCall, 2001, 2005; Museus & Griffin, 2011; Solórzano et al., 2005; Villalpando, 2003, 2004; Zuberi, 2001) to understand how all students express academic success by standard reporting measures, not only Native students. While these results reveal a disparity between Native and non-Native students as the biennial “achievement gap” reporting already does, it may also reveal disparity for individual groups of students to which Montana is not currently aware. Prior to implementing use of the saturated models, contrast coding, specifically effect coding (Daly, Dekker & Hess, 2016), is utilized to compare each level of the race, gender and class variables to the grand mean.

As the opportunity factors of student mobility and poverty are woven into the regression stories, this study considers the social-spatial geography of schools to better understand the structural and institutional factors associated with power and place (Solórzano & Veléz, 2016) impacting students’ relationships to academic success. While there is an abundance of inequalities which impact student performance (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010), this study focuses on two opportunity factors prominent for Native students in Montana

which are also geographically informed. This study appropriately utilizes Multilevel Modeling (MLM) to examine the impact of poverty and student mobility, as prevalent student opportunity factors impacting access to academic success (academic achievement and academic completion) for a within-group sample of Native students. Education data are inherently clustered as students are nested within schools. MLM is the traditional statistical approach for adjusting for clustering of students within schools (Raudenbush & Bryk, 2002). Using the exploratory school-level SIDE poverty metrics for Montana high schools (NCES, 2021a), the study investigates how student mobility, while accounting for individual student characteristics and school-level factors, impact student academic achievement and academic completion, considering both school-level differences and varying effects of poverty across schools.

### Research Context

Many of the proximal factors in this study are covered in the literature review and utilized as control variables (see full description in Control Variables sections). In addition to factors such as social location, English Learner status, and school environment aspects such as rurality, the supports and opportunities for students within their school environment are a proximal factor potentially impacting students in the sample. Particularly for Native students— a focus within-group of the study due to existing “achievement gap” policy and reporting— there are school supports and opportunities. Montana education not only is dedicated to the education of Montana Indigenous cultures and relevance in all of its K-12 schools through IEFA, but schools across the state provide additional programs uniquely for the Native student population both on- and off-reservation. Some of these may include Head Start programs, tribal education specialists, and Native specific advisors. While many of these programs are offered to Native

students both on- and off-reservation, some may only be accessible based on location. The interests and priorities of the supports provided to Native students may vary and the effect of these external factors may impact this study. The sample of Native students was collected across all Montana public schools, both on- and off-reservation, so the structural, community, cultural, and relational contexts of the sites from where the data was collected will vary. Not only are these contexts varied between on and off-reservation locations, but also between on-reservation schools and communities.

The cultural and social distal factors of a student's surrounding educational environment immediately impact their experience. Bosman and Kunnen (2001) pushed for a continuous identity formation concept where identity is composed through short-term recurring transactions (Bosman & Kunnen 2001; Schwarts et al., 2011) between the individual and their environment. In this way, identity is thought of as a process (Schwartz et al., 2011). In noting the environments in which students engage with identity formation, there must be consideration for the social aspects of the learning environment and the means in which social interaction impacts learning and identity formation itself. In fact, social identity formation (Postmes et al., 2005; Postmes, et al., 2006) describes how individuals will negotiate their values to each other's when in a working group. Factors which disrupt the process of identity and social identity formation, such as school mobility, negatively impact participation, presence, and achievement. For many Native students in Montana, their cultural and social identities within their community and family experience have powerful influence over the academic experience. Considering high mobility rates are more common in high poverty and low-income contexts, socioeconomics as a distal factor is also of consideration.

Political forces such as the reauthorization of ESEA as Every Student Succeeds Act (ESSA) in 2015 under the Obama administration, as well as Montana's adoption of its Consolidated State Plan in 2018 were likely forces that impacted the cohort of students in the 11th and 12th grade years of school. ESSA reignited an emphasis on standardized assessment data collection at the local level and college and career preparedness. Given the ACT is the predominant and required assessment measuring college readiness, it may have served to increase the educational aspiration of students.

This study utilized data for one graduating cohort spanning 2015-2016 to 2018-2019 school years. In this way, the dataset avoids focus on the COVID pandemic and the significant array of distal and proximal factors that impacted students' experiences. This is particularly important when considering the mobility patterns of students. Remote learning essentially halted movement of students between schools, and lockdown protocols certainly impacted students' movement between towns, neighborhoods, and homes. In addition, unemployment during the recession to follow significantly impacted students individual, familial and school relationships and experiences to poverty. The avoidance of the COVID-impact years is in effort to isolate the phenomenon and turn toward more anticipated trends.

#### Data Collection Procedures

All data is collected through the Montana AIM Student Information System. AIM is a system designed to collect demographic, enrollment, program participation, and assessment data on every student enrolled in a Montana public school and is informed by Montana school systems' local level Student Information Systems (e.g. Infinite Campus, Power School, etc.). AIM data is stored in a longitudinal data warehouse. Queries were generated by the researcher

using SQL to pull the data directly from the warehouse. These queries were submitted as a suggested template along with a research proposal application to the OPI and reviewed in a data security committee. The data request was fulfilled and dataset pulled by an OPI colleague separate from the project, and further exported and shared back to the researcher as a deidentified Excel file ensuring the protection of student PII. This file is saved on a password protected computer in a password protected office.

### Population & Sample

The population is all grade 11 students during the 2018 fiscal year and all grade 12 (or graduating) students during the 2019 fiscal year in Montana. The intended sample for this study contains a complete representative sample from AIM – where representation is across gender, racial categories, poverty classification, and school locations. The probability of achieving a representative sample that can be generalizable of the population is high (Mills & Gay, 2019) because the method pulls from all students in the state’s public school system, however there are some limits to the strategy. First, AIM data is only representative of students enrolled in the state’s public school system. Therefore, any student enrolled in a private, homeschool, or non-public institution are not represented. The sample also contains only those students whose public educational experience remained in Montana public schools, therefore any student who moved out of state, moved to a non-public system, or another reason, are not represented in the sample.

Merging AIM data with the school poverty dataset generated from the Blindsight application by matching to school number (a unique school identifier), the matched sample ( $n = 10,505$ ) contains students from the 2019 graduating class who either graduated within their cohort (traditional four year senior), graduated outside of their cohort (non-traditional fifth year

senior), dropped out, or failed to graduate within their cohort but remained enrolled to pursue non-traditional graduation in 2020. These students were aligned to their ACT composite score from their junior year ACT assessment. School location is based on their enrollment in 2019. All public Montana high schools are included in the sample. Montana high schools not included are private or religious institutions, behavioral health specialty schools, correctional facilities, Indian bureau schools, the Montana School for the Deaf and Blind, and students in the Montana State Prison.

In the matched dataset there are 884 students who either graduated as a non-traditional senior (non-traditional graduate), or who did not graduate with their 2019 cohort but elected to continue on as a non-traditional student with the 2020 cohort (continued). In the final dataset utilized, only cohort graduates and dropouts remained in the sample ( $n = 9,621$ ). The decision to keep only cohort graduates rather than any completer type is most closely aligned to existing “achievement gap” reporting as the biennial report in Montana only compares cohort graduation rates between Native and non-Native students. There are significant limitations to removing non-cohort graduates and those who continue on, especially in understanding Native student academic success and completion. Among the American Indian/Alaskan Native students ( $n = 1,051$ ) in the matched dataset, 186 students (17.70 percent) elected to continue on as a non-traditional senior in 2020 and 42 (4.00 percent) students graduated as a non-traditional graduate. Combined, removing these two end statuses effectively removed about 20 percent of American Indian/Alaskan Native students from the sample. Similarly, when considering geospatial context for many Native students, 133 (17.16 percent) of students attending a school off-reservation elected to continue on and 36 (4.65 percent) graduated as a non-traditional graduate. Combined,

removing the end status of continued and nontraditional graduate removed over 20 percent of Native students attending an off-reservation school from the final sample.

### ANOVA of Academic Completion Outcome Variable

ANOVA was utilized to determine if there are statistical differences between kinds of end status for students by examining the relationships that academic completion for the matched dataset (cohort graduates, dropouts, nontraditional graduates, continued on) has to academic achievement (composite ACT score), school poverty and student mobility. These results are compared to the same relationships but when academic completion is manipulated to be a binary outcome (cohort graduates and dropouts). The analysis of variance indicated there are significant differences among the four academic completion types in the matched dataset to ACT composite score ( $F(3, 9,155^2) = 117.4, p < .0001$ ), school poverty ( $F(3, 10,501) = 17.45, p < .0001$ ), and student mobility ( $F(3, 10,501) = 25.77, p < .0001$ ). In comparison, the analysis of variance indicates noteworthy differences among these relationships after end status types for non-traditional graduates and those students who continued on as a non-traditional graduate in 2020. The analysis of variance reveals there are significant differences among the binary academic completion types in the final dataset to ACT composite score ( $F(1, 9,619) = 89.88, p < .0001$ ). When academic completion was reduced to a binary outcome, the variation in ACT scores persists even when the completion score is simplified. Significant differences were also observed in student mobility ( $F(1, 9,619) = 58.78, p < .0001$ ) between these two groups, suggesting that mobility continues to play a role in academic outcomes even in the binary context. However, the analysis of variance also indicates the relationship to school poverty is no longer significant ( $F(1,$

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<sup>2</sup> 1,346 observations are missing an ACT composite score. See section on handling missing data.

9,619) = 0.077,  $p = 0.781$ ). This change suggests that when academic completion is simplified to a binary variable, school poverty does not significantly differentiate between graduates and dropouts. These results call for the need to consider completion types outside of cohort graduation and dropout as standard “achievement gap” reporting in Montana currently mandates. Future research should consider analysis through use of a nominal logistic regression to explore the outcome variable of academic completion as cohort graduates, non-traditional graduates, dropouts and those students who continue on as non-traditional graduates rather than simply a binary outcome.

### Variables

This study functions in two stages. First, this investigation utilizes López and team’s (2018) intersectional methodology as part of the expanding field of QuantCrit. Estimates for saturated regression models examining the outcome measures by social locations are calculated. The marginal effects, which would inform how the outcome measure changes when social locations change, are reported for all combinations of social location, which are based on race-ethnicity (federal race/ethnicity codes; categorical), gender (male/female; binary) and student poverty (free and reduced price lunch participation; binary), where the reference group is white, low-level poverty, female students. The categorical variable for race in this study uses the five federal categories, as well as categories for students who identify as Hispanic and Multiracial. The binary variable for student-level poverty in this study uses free and reduced price lunch (FRPL), in which case a student-level variable is transformed by acknowledging students who receive free or reduced lunch as high-level poverty and students who are not eligible as low-level poverty. Table 3 articulates the 28 social locations utilized. In this way, the first stage utilizes

two dependent variables and three independent variables. Contrast coding, specifically effect coding (Daly et al., 2016) compares each level of the race, gender and class variables to the grand mean. The focus of the first stage is to reveal student inequalities that are unnoticed in conventional modeling and reporting around the “achievement gap” policy and discourse.

Table 3. Race-Gender-Class Social Locations of Montana High School Students

<b>Race</b>	<b>Class</b>
Hispanic	High-level poverty
Hispanic	Low-level poverty
American Indian or Alaska Native	High-level poverty
American Indian or Alaska Native	Low-level poverty
Asian	High-level poverty
Asian	Low-level poverty
Black or African American	High-level poverty
Black or African American	Low-level poverty
Native Hawaiian or Other Pacific Islander	High-level poverty
Native Hawaiian or Other Pacific Islander	Low-level poverty
White	High-level poverty
White	Low-level poverty
Multiracial	High-level poverty
Multiracial	Low-level poverty

<b>Race</b>	<b>Gender</b>	<b>Class</b>
Hispanic	Male	High-level poverty
Hispanic	Female	Low-level poverty
American Indian or Alaska Native	Male	High-level poverty
American Indian or Alaska Native	Female	Low-level poverty
Asian	Male	High-level poverty
Asian	Female	Low-level poverty
Black or African American	Male	High-level poverty
Black or African American	Female	Low-level poverty
Native Hawaiian or Other Pacific Islander	Male	High-level poverty
Native Hawaiian or Other Pacific Islander	Female	Low-level poverty
White	Male	High-level poverty
White	Female	Low-level poverty
Multiracial	Male	High-level poverty
Multiracial	Female	Low-level poverty

Second, non-saturated regression models are explored where the independent variable is mobility on a within-group sample of Native only students. The second stage of this study utilizes MLM to better understand the impact of poverty and mobility as a geographically informed variables on academic achievement by considering nesting in schools. A robust linear MLM model is used where the outcome variable as academic achievement (composite ACT score), and a robust logistic MLM model is used where the outcome variable is academic completion (graduate/dropout). For both, student (gender, student poverty, English Learner status) and school (school poverty, rurality, on/off reservation status, Title 1 status, Native student density) controls are set with incorporating the predictors. In this way, the second stage

utilizes two dependent variables, mobility as an independent variable, three student controls, and five school controls. The focus of the second stage is to illuminate how poverty and mobility as a geographically experienced phenomenon impact the standardized metrics (academic achievement and completion) of “achievement gap” reporting. Each variable is described in detail in Table 4.

Table 4. Table of Specifications for Variables in the Study

Variable	Variable Type	Operationalization	Measurement
reservation status	dichotomous	0=off reservation, 1=on reservation	0,1
school rurality	nominal	1=urban 2=urban cluster 3=rural < 25 miles 4=rural > 25 miles	1-5
Title 1 status	nominal	1= eligible not participating 2= not eligible 3=School wide program 4= Target assistance	1-4
Native student density	nominal	1= 0-24% 2= 25-49% 3= 50-74% 4=75-100%	1-4
Binary Native student density	binary	0=low density=0-49% 1=high density=50-100%	0,1
gender	dichotomous	0=male, 1=female	0,1
race	nominal	1=Hispanic/Latino, 2=American Indian or Alaskan Native, 3=Asian, 4=Black or African American, 5=Native Hawaiian or Other Islander, 6=White, 7=Multiracial	1-7
student poverty	dichotomous	0=not eligible/low-level poverty, 1=free or reduced lunch/high-level poverty	0,1
English Learner status	nominal	0=not English Learner 1=current English Learner 2=former English Learner	0,1, 2
school poverty	continuous	BlindSIDE income-to-poverty ratio (IPR) values	0-999
student mobility	categorical	0=same system	0-4

		1=1 system 2=2 systems 3=3 systems 4=4+ systems	
binary student mobility	binary	0=no mobility 1=mobility	0,1
academic achievement	continuous	composite score on the ACT assessment	0-36
academic completion <sup>3</sup>	nominal	0=dropped out 1=graduated 2=nontraditional graduated 3=continued	0, 1, 2, 3
binary academic completion	binary	0=dropped out 1=graduated	0,1

In this study's final sample (n = 9,621), the majority of students identify as white (82.65 percent), while the second largest racial category includes students who identify as Native (American Indian/Alaskan Native and Multiracial) at 8.55 percent. Most students successfully graduate within their cohort (94.84 percent), with only 496 students recorded as dropouts. The mean school poverty level across the sample of students is 279.20, and approximately 33 percent of students experience high levels of individual poverty. The proportions of students attending schools by location parallel expected distributions, with about 94 percent of students attending schools off-reservation with low Native student density, and around 6 percent attending schools on-reservation with high Native student density. The mean ACT score across the sample is 19.71, which is 2.29 points below the college readiness benchmark. Additionally, the norm for students

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<sup>3</sup> The outcome variable for end status or academic completion is transformed and further manipulates the dataset to function as a binary outcome, only including students who drop out (0) and students who graduate (1) in the final dataset.

in this sample is to not experience mobility (84.91 percent), meaning the majority attend the same high school all four years. Table 5 provides complete descriptive statistics for the sample.

Table 5. Descriptive Statistics of Variables for the Study

<i>Sample Size</i>	<i>n</i> = 9,621		
<b>Continuous Variables</b>			
	<i>M</i>	<i>SD</i>	<i>R</i>
<i>Academic Achievement</i>	19.71	4.73	5 to 36
<i>School Poverty</i>	279.20	70.10	98 to 412
<b>Categorical Variables</b>			
<i>Academic Completion</i>	Dropped Out = 496 (5.16%) Graduated = 9,125 (94.85%)		
<i>Binary Student Mobility</i>	Mobility = 1,452 (15.10%) No Mobility = 8,169 (84.91%)		
<i>Student Mobility</i>	Same System = 8,169 (84.91%) 1 System = 1,033 (10.74%) 2 Systems = 313 (3.25%) 3 Systems = 80 (0.83%) 4+ Systems = 26 (0.27%)		
<i>Gender</i>	Female = 4,729 (49.15%) Male = 4,892 (50.85%)		
<i>Race</i>	American Indian/Alaskan Native = 823 (8.55%) Asian = 72 (0.75%) Black = 97 (1.01%) Hispanic = 382 (3.97%) Multiracial = 267 (2.78%) Native Hawaiian/Pacific Islander = 28 (0.29%) White = 7,952 (82.65%)		
<i>Student Poverty</i>	Low Poverty (Not Eligible for FRPL) = 6,429 (66.82%) High Poverty (FRPL Eligible) = 3,192 (33.18%)		
<i>English Learner Status</i>	Current English Learner = 108(1.12%) Former English Learner = 180 (1.87%) Not English Learner = 9,333 (97.01%)		
<i>Native Student Density</i>	0-24% Native student population = 8,790 (91.36%) 25-49% Native student population = 182 (1.89%) 50-74% Native student population = 160 (1.66%) 75-100% Native student population = 489 (5.08%)		

<i>Binary Native Student Density</i>	0-49% Native student population = 8,972 (93.25%) 50-100% Native student population = 649 (6.75%)		
<i>School Rurality</i>	Rural (< 25 miles) = 1,155 (12.00%) Rural (> 25 miles) = 1,989 (20.67%) Urban = 2,549 (26.49%) Urban Cluster = 3,928 (40.83%)		
<i>Title 1 Status</i>	Eligible, not participating = 398 (4.14%) Not eligible = 2,290 (23.80%) School-wide program = 3,350 (34.82%) Target Assistance = 3,583 (37.24%)		
<i>Reservation Status</i>	Off reservation = 9,015 (93.70%) On reservation = 606 (6.30%)		
<i>Sample Size</i>	$n = 9,621$		
<b><i>Continuous Variables</i></b>	<i>M</i>	<i>SD</i>	<i>R</i>
<i>Academic Achievement</i>	19.71	4.73	5 to 36
<i>School Poverty</i>	279.20	70.10	98 to 412
<b><i>Categorical Variables</i></b>			
<i>Academic Completion</i>	Dropped Out = 496 (5.16%) Graduated = 9,125 (94.85%)		
<i>Binary Student Mobility</i>	Mobility = 1,452 (15.10%) No Mobility = 8,169 (84.91%)		
<i>Student Mobility</i>	Same System = 8,169 (84.91%) 1 System = 1,033 (10.74%) 2 Systems = 313 (3.25%) 3 Systems = 80 (0.83%) 4+ Systems = 26 (0.27%)		
<i>Gender</i>	Female = 4,729 (49.15%) Male = 4,892 (50.85%)		
<i>Race</i>	American Indian/Alaskan Native = 823 (8.55%) Asian = 72 (0.75%) Black = 97 (1.01%) Hispanic = 382 (3.97%) Multiracial = 267 (2.78%) Native Hawaiian/Pacific Islander = 28 (0.29%) White = 7,952 (82.65%)		
<i>Student Poverty</i>	Low Poverty (Not Eligible for FRPL) = 6,429 (66.82%) High Poverty (FRPL Eligible) = 3,192 (33.18%)		

<i>English Learner Status</i>	Current English Learner = 108(1.12%) Former English Learner = 180 (1.87%) Not English Learner = 9,333 (97.01%)
<i>Native Student Density</i>	0-24% Native student population = 8,790 (91.36%) 25-49% Native student population = 182 (1.89%) 50-74% Native student population = 160 (1.66%) 75-100% Native student population = 489 (5.08%)
<i>Binary Native Student Density</i>	0-49% Native student population = 8,972 (93.25%) 50-100% Native student population = 649 (6.75%)
<i>School Rurality</i>	Rural (< 25 miles) = 1,155 (12.00%) Rural (> 25 miles) = 1,989 (20.67%) Urban = 2,549 (26.49%) Urban Cluster = 3,928 (40.83%)
<i>Title 1 Status</i>	Eligible, not participating = 398 (4.14%) Not eligible = 2,290 (23.80%) School-wide program = 3,350 (34.82%) Target Assistance = 3,583 (37.24%)
<i>Reservation Status</i>	Off reservation = 9,015 (93.70%) On reservation = 606 (6.30%)

Missing data exists across one variable in the dataset: academic achievement (composite ACT scores). There is 9.54 percent ( $n = 918$ ) of students missing an ACT score who had an end status of either dropping out or graduating within the 2019 cohort in the sample ( $n = 9,621$ ). Most students (63.29 percent) with missing ACT scores remained at the same school system during their high school experience. These students attended schools with a mean school poverty measure of 279.80 which is about 0.6 IPR value points higher than the mean school poverty for the whole sample. The majority of these students attend a school off-reservation with low Native density— a school whose Native student population is 0 to 24 percent. About half (50.76 percent) of students missing an ACT score experience high poverty as defined by their FRPL eligibility. Overall, these students had higher proportions of students dropping out compared to the whole sample. Most notably, 25.82 percent of students missing an ACT score dropout, where in

comparison, only about 5 percent of the whole sample dropout. Table 6 below provides descriptive statistics for students missing an ACT score.

Table 6. Descriptive Statistics of Missing Data for the Study

<i>Missing ACT Score</i>	<i>n = 918</i>
<i>School Poverty</i>	<i>M = 279.8, SD = 88.43, R = 98 to 412</i>
<i>Academic Completion</i>	Dropped Out = 237 (25.82%) Graduated = 681 (74.18%)
<i>System Mobility</i>	Same System = 581 (63.29%) 1 System = 223 (24.29%) 2 Systems = 86 (9.37%) 3 Systems = 21 (2.29%) 4+ Systems = 7 (0.76%)
<i>Gender</i>	Female = 440 Male = 478
<i>Race</i>	American Indian/Alaskan Native = 139 Asian = 10 Black = 11 Hispanic = 52 Multiracial = 31 White = 671 Native Hawaiian/Pacific Islander = *
<i>Student Poverty</i>	Low Poverty (Not Eligible for FRPL) = 452 High Poverty (FRPL Eligible) = 466
<i>English Learner Status</i>	Current English Learner = 29 Former English Learner = 24 Not English Learner = 865
<i>Native Student Density</i>	0-24% Native student population = 801 25-49% Native student population = 11 50-74% Native student population = 11 75-100% Native student population = 95
<i>School Rurality</i>	Rural (< 25 miles) = 86 Rural (> 25 miles) = 178 Urban = 269 Urban Cluster = 385
<i>Title 1 Status</i>	Eligible, not participating = 23 Not eligible = 239 School-wide program = 367

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Target Assistance = 289

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*Reservation Status*      Off reservation = 817  
   On reservation = 101

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\*Indicates scenarios where the count of students is masked to protect student identity.

Missing ACT scores were first replaced by the mean ACT for the sample ( $M = 19.71$ ). It is concluded mean replacement is an inadequate method for this sample. Because about 9.5 percent of the sample receives the mean, it in turn manipulates the sample density (see Figure 2 in Appendix). Listwise and pairwise deletion methods are also avoided as they tend to produce standard errors that are too large or too small, respectively (Van Buuren, 2018). Rather, multiple imputation is the procedure utilized in this study to handle missing ACT scores. Multiple imputation (Rubin, 1987; 1996) creates multiple complete datasets where the missing values are imputed based on the observed data, effectively replacing the missing values with plausible data (Van Buuren, 2018). Multiple imputation was employed using the ‘mice’ package in R. Given the potential impact of missing ACT scores ( $\sim 9.5\%$ ) on the analysis, 10 imputed datasets were created to ensure robustness in the results. Imputation was conducted using the Predictive Mean Matching (PMM) method, which is particularly useful for handling missing continuous data by matching each missing value with observed values for similar cases. Imputation was run for a maximum of 50 iterations and random seed set at 123 for reproducibility. All relevant variables were included in the imputation model, and after the imputation process results were pooled using Rubin’s rules to combine estimates and standard errors. After multiple imputation, mean ACT decreased ( $M = 19.65$ ). The density plot of ACT after multiple imputation presents what is accepted as normal distribution in this study, see Figure 3 in the Appendix.

### Dependent Variables

Academic Achievement. This variable reflects the focus of utilizing students' standardized assessment performance as a primary metric for measuring the Native to non-Native "achievement gap" in Montana's biennial reporting. The report examines Smarter Balanced performance (grades 3-8) and ACT performance (grade 11), but because the sample for this study is of high school students only, academic achievement is captured only through ACT composite scores. In this way, the variable for academic achievement is continuous where scores range from 5 to 36. For this sample, the mean 11th grade ACT composite score is 19.65 after multiple imputation to handle for 918 missing ACT scores, which is below the state defined indicator for college readiness. The density plot for ACT composite score after multiple imputation presents a fairly normal distribution (see Figure 3 in the Appendix) and is accepted as close to normal in this study.

Academic Completion. This variable reflects the focus of utilizing students' graduation success as a primary metric for measuring the Native to non-Native "achievement gap" in Montana's biennial reporting where one limitation is utilizing only cohort graduation. This study utilizes students who complete high school as part of the 2019 cohort graduation and those students who dropout. In this study there were  $n = 9,125$  total students who graduated in the 2019 cohort. In this study there were also  $n = 496$  students who dropped out.

The majority of students experience graduation (94.84 percent) as their end status, where the remaining students dropped out (5.16 percent). Of students attending school off-reservation, 95.02 percent graduated within their cohort, and similarly, on-reservation 92.24 percent graduated within their cohort. Similarly, when continuing exploration by school locations, 94.99 percent graduated within their cohort at low Native student density schools, and 92.02 percent of

students attending a school with 75-100 percent Native student population graduated. About 90 percent of students (91.70) experiencing high poverty graduated within their cohort, and over 95 percent (96.41) of students experiencing low poverty graduated within their cohort.

### Independent Variables

Student Poverty. While poverty measures do not sufficiently capture all challenges a student faces in their opportunity to learn, poverty measures focus attention on the economic disadvantage a student navigates. Student-level poverty in this study is captured using a proxy measure. Education research has historically measured socioeconomic status (SES) with National School Lunch Program (NSLP) counts of students eligible for free or reduced-price lunch (FRPL). In this way, this study understands student-level poverty as a binary variable where students who qualify for FRPL are considered high poverty and students not eligible or not participating in FRPL are considered low poverty. Across the sample, 33.92 percent ( $n = 3,192$ ) qualified as high poverty while 66.82 percent ( $n = 6,429$ ) were low poverty. Considering students who graduated in 2019, 32.08 percent were receiving either free or reduced priced lunch (high poverty). In comparison, 53.43 percent of students who dropped out were high poverty. Utilizing a Pearson's chi-squared test, a student's poverty as defined by FRPL indicates a statistically significant ( $<.001$ ) but very weak ( $0.1003$ ) relationship to end status. The mean ACT score for students in high poverty ( $M = 17.86$ ) is almost 3 (three) points lower than the mean ACT score for students in low poverty ( $M = 20.62$ ) (see Figure 3 in Appendix). Almost 25 percent of high poverty students experience mobility, while only 10.36 percent of low poverty students experience mobility.

Significant limitations exist when utilizing the proxy NSLP poverty measure. NSLP data has been used as the primary measure for economic disadvantage in the field of education. However, many schools no longer require families to report income data, such as in Community Eligibility Provision (CEP) districts. In CEP districts, all students are eligible for school breakfast and lunch meals essentially transforming NSLP data into a school-level measure. Alternative poverty measures most often utilize geographic data such as Census Blocks where 300-6,000 people are defined within a polygon space by income data. One limitation is often these polygons do not align with neighborhood boundaries. Particularly in states like Montana, rural areas are often obscured, especially for those areas on tribal or reservation lands. The Small Area Income Poverty Estimate (SAIPE) from the Census Bureau utilizes this form of geographic data with the school district as the unit of analysis, but cannot be disaggregated at the school-level (Clausen, 2022). While a proxy, FRPL remained the most effective student measure.

School Poverty. In 2019, Montana was one of 15 states to receive supplemental funding for its Statewide Longitudinal Data System (SLDS) to explore alternatives for a student-level poverty indicator. As part of this project, Montana evaluated use of statistically modeled household income estimates from the National Center of Education Statistics' (NCES) Spatially Interpolated Demographic Estimates (SIDE) Project (NCES, 2021a). The SIDE Project utilizes the latitude and longitude of student home addresses to estimate a household income. SIDE aligns the student's address to the 25 nearest households in the U.S. Census's American Community Survey (ACS), weighting income by proximity of the address location to neighborhood income (NCES, 2021a). Based on an evaluative follow up study by OPI, the SIDE estimates were found to be highly correlated to existing NSLP data, but the magnitude of the

SIDE student values regarding impact on achievement outcome measures was significant and greater than NSLP eligibility (Clausen, 2022). SIDE measures also utilize ACS data on household and neighborhood characteristics which is an attribute missing from NSLP data.

One major limitation of the developing SIDE student-level poverty measure in Montana is restricted access to student address data. Montana does not require schools to report student addresses to the state. In this way, ensuring accurate addresses for students across the sample utilized in this study is unrealistic. Due to this limitation, use of NSLP data provided the most accurate student-level poverty indicator. While this study is unable to use SIDE measures at the student-level, it is able to utilize SIDE measures at the school-level using accurate school addresses. The school-level poverty variable in this study articulates relative income levels on a continuous scale ranging from 0 to 999, where schools with a score of 130 or less would meet the threshold for free school lunch and a score of 131 to 185 would qualify for reduced-price lunch. The mean school poverty score in the sample was an IPR value of 284.31. The school-level SIDE measures used in this study were pulled from the BlindSIDE application in 2019 for 170 high schools with scores ranging from 98 to 542.

Analysis of outliers across academic achievement (ACT composite score) and school poverty was conducted using three methods: (1) evaluation of interquartile range (IQR) values by defining outliers as 1.5 times the IQR above the third quartile and below the first quartile, (2) identifying a z-score threshold of a score greater than 3 or less than -3, and (3) utilizing a modified z-score as a robust method less sensitive to outliers than the standard z-score by using the median and median absolute deviation (MAD). Across all three of the continuous variables and across the three methods for identifying outliers, school poverty was the only element to

present an outlier—the lowest poverty school with an IPR value of 542—that would need identification and handling. There was one school in the sample whose poverty metric was an outlier. Rather than remove the school, its school poverty value was replaced with the mean across the other three schools in that district ( $M = 324$ ). Likely this school's IPR value was inflated due to its location in a dense urban and university neighborhood. After handling this school as an outlier, the mean IPR value for the sample decreased ( $M = 279.22$ ) and the range naturally adjusted as well (98 to 412).

The density plot for school poverty presents a fairly normal distribution (see Figure 4 in the Appendix) with reasonable dispersion measures accepted as normal in this study. The slight negative skew (-0.13) indicates the mean is pulled toward lower values, or in this case, schools in higher poverty areas with lower IPR values. The distribution's kurtosis (-0.52) suggests the distribution has lighter tails than a normal distribution and that the data is less extreme with few outliers. Examining the relationship between ACT and school poverty, there appears to be a positive linear relationship where students with higher ACT scores are also more likely to attend a school with a higher IPR value, and vice a versa (see Figure 5 in Appendix). Considering the relationship between end status and school poverty, students who dropout attend schools with a slightly lower IPR value (275.78) compared to their peers who graduate (279.41) (see Figure 6 in Appendix).

Mobility. Student mobility patterns are captured as total unique school system enrollments over the course of the four-year time period or all four years of high school for the 2019 cohort. Despite the risk on time-series agreement, this study seeks to align to existing mobility research which argues the importance of measuring mobility across the academic

experience when examining various performance outcomes such as graduation and achievement (Engel, 2006). Considering the academic outcome of graduation, existing research associates the cumulative impact of multiple school changes across school years increases the risk of dropout (Rumberger & Larson, 1998). Similarly, literature also emphasizes the negative effects of student mobility on educational outcomes like assessment and urges the importance of considering mobility over time (Swanson & Schneider, 1999). In this way, the independent variable of student mobility, measured across all four years of high school as a cumulative measure, is a predictor for performance on the ACT students' Junior year and their academic completion as a graduate or dropout.

Mobility is originally measured as a continuous variable where the numerical value for each student represents the total number of unique non-structural school enrollments. In this way, when mobility is 0, the student remained in the same school system across all four years. As a continuous variable, students' unique school enrollments range from 0 to 6, or in other words range from remaining in the same high school all four years to having upwards of 6 different schools attended throughout the same timeframe. The average frequency of mobility in the sample is representative of essentially remaining in the same school ( $M = 0.24$ ). The density plot for mobility (see Figure 7 in the Appendix) presents negative skewness in the distribution with most students experiencing little mobility as the norm. Extreme kurtosis naturally also exists where the leptokurtic distribution indicates a much higher peak and heavier tail toward school enrollments greater than 1 indicating an impact on analysis and interpretation of results. Examining mobility as a continuous variable, it is concluded transformation of mobility to a categorical variable is required, similar to Henneberger and team (2023). In this study, mobility

is transformed from a continuous variable ranging from 0 to 6 unique school enrollments throughout high school, to instead a categorical variable where 0 school moves is coded as “Same System”, 1 school move as “1 System”, 2 school moves as “2 Systems”, 3 school moves as “3 Systems” and students with 4 to 6 school moves are coded as “4+ Systems.” Additionally, mobility is also transformed to a binary variable where students who had 0 unique non-structural enrollments, or who remained in the same system all four years, were coded as “No Mobility.” In comparison, any student with 1 or more unique non-structural enrollments were coded as having experienced “Mobility,” see Table 7 below.

**Table 7. Descriptive Statistics of Mobility Transformed as a Categorical and Binary Variable**

<i>Mobility</i>	Same System = 8,169 (84.91%) 1 System = 1,033 (10.74%) 2 Systems = 313 (3.25%) 3 Systems = 80 (0.83%) 4+ Systems = 26 (0.27%)
<i>Binary Mobility</i>	No Mobility = 8,169 (84.91%) Mobility = 1,452 (15.09%)

In alignment to Henneberger and team (2023), analysis utilizes mobility as a binary variable in this study. Most students do not experience mobility as part of their academic experience for the 2019 graduating cohort. It is important to note, similar to existing research, there are greater proportions of students experiencing mobility who are of higher poverty and racial minorities. Of students experiencing high poverty, almost 25 percent experience mobility where only about 10 percent of low poverty students experience mobility. Additionally, while only about 13 percent of white students experience mobility, approximately 32 percent of American Indian/Alaskan Native and 24 percent of Black students experience mobility. Considering an aspect of students’ location, on-reservation (23.60 percent) students experience mobility more than off-reservation (14.52 percent) students.

Considering the outcome variables of academic completion and academic achievement, students' mobility seems to share a relationship with student success to some degree. Utilizing a Pearson's chi-squared test and Cramer's V, whether students experience mobility shares a statistically significant ( $<.01$ ) but weak (0.133) relationship to academic completion. The mean ACT composite score for students experiencing mobility is 17.49 while students not experiencing mobility is 20.04 (see Figure 8 in the Appendix). Mobility also seems to present a relationship to school poverty as students who experienced mobility attend schools with a mean IPR value of 265.00 while students who did not experience mobility attend schools with a mean IPR value of 281.75 (see Figure 9 in the Appendix).

#### Student-level Control Variables

Race. The majority of the sample identifies as white (82.65 percent), and the second largest category by race is students who identify as Native (American Indian/Alaskan Native and Multiracial) at 8.55 percent. Almost 95 percent of students who identified as white graduated within the 2019 cohort as a traditional 4-year senior. About 90 percent of Native students graduated within the 2019 cohort. Utilizing a Pearson's chi-squared test and Cramer's V, a student's racial identity shares a statistically significant ( $<.001$ ) but very weak (0.079) relationship to end status. The mean ACT score for white students ( $M = 20.19$ ) is above the mean for the sample. The highest mean by racial categories is for Asian students ( $M = 21.68$ ) compared to the lowest mean by racial categories which is for American Indian/Alaskan Native students ( $M = 15.86$ ) (see Figure 10 in the Appendix). American Indian/Alaskan Native students (31.96 percent), Native Hawaiian/Pacific Islander students (25.00 percent) and Black students (23.71 percent) have the greatest proportions of students experiencing mobility. The remaining groups

of students by racial categories have less than 20 percent of students experiencing mobility (Asian = 8.33 percent; Hispanic = 19.63 percent; Multiracial = 19.85 percent; White = 12.89 percent).

Gender. There is a representative split by gender in the sample, where about 49 percent of the sample is female. While the share of graduates by gender was proportional, male students had a higher proportion of student dropout outcomes: About 64 percent of dropouts were male. Utilizing a Pearson's chi-squared test, a student's gender shares a statistically significant ( $<.001$ ) but very weak (0.061) relationship with end status. The mean ACT score for males ( $M = 19.39$ ) and for females ( $M = 20.04$ ) display similar distributions of academic achievement (see Figure 11 in Appendix). Males (13.43 percent) and females (16.91 percent) also present similar proportions of students experiencing mobility, though females perhaps experience mobility more than males. Utilizing a Pearson's chi-squared test, a student's gender shares a statistically significant ( $<.001$ ) but very weak (0.047) relationship with mobility.

Student Poverty. See elaboration of descriptive statistics in the Independent Variables section above.

English Learner Status. The variable of English Learner (EL) status is included in this study considering the relationship to ESSA which mandates assessment of ELs after a student has been in the U.S. for one year. The Home Language Survey reveals German (0.34 percent), Spanish (0.21 percent), and Native Indigenous languages (less than 1 percent) are spoken across Montana homes, as noted in the Review of Literature in this paper. Of EL students who identify as American Indian or Alaskan Native or multi-racial in Montana, hardly 1 percent have been English proficient since the release of Montana's Consolidated State Plan in 2018 (GEMS,

2023a). In this sample, 25.88 percent of American Indian/Alaskan Native students are currently or formerly an EL. The majority of students in the sample have never been an English Language Learner (97.01percent) and score a mean of 19.85 on the ACT which is just slightly above the mean for the entire sample. While students who either are currently or formerly an English Language Learner only comprise 2.99 percent of the sample, it is notable their mean ACT score ( $M = 14.52$ ) is over 4 points lower (see Figure 12 in Appendix) compared to their peers.

### School-level Control Variables

This sample captures the reality of Native students' school locations where on-reservation schools are primarily populated by Native learners. A Pearson's chi-squared test ( $<.001$ ) indicates a statistically significant relationship between school's reservation status and density of Native student population. In addition, Cramer's V (0.8303) indicates a very strong substantive relationship between the two variables. In this way, students with 50 percent or higher Native student density are more likely to be attending a school on-reservation, and inversely, off-reservation schools are more likely to have a low Native student population (see Figure 13 in Appendix). However, a relationship to a school's rurality is not as prevalent where the chi-squared test ( $<.001$ ) indicates a significant but weak relationship (0.2137) between reservation status and rurality. Similarly, the relationship between a school's rurality and Native student density presents a significant ( $<.001$ ) but very weak relationship (0.1703).

School Rurality. In this study, rurality is defined in relation to urban areas. In which case, an urban area is defined as a territory inside an urbanized area and inside a principal city in Montana or is less than 10 miles from an urbanized area. An urban cluster includes those areas to the perimeter of an urban territory that is more than 35 miles away from an urbanized area. The

two rural codes for school rurality are defined in proximity to an urbanized areas either less than 25 miles, and over 25 miles. In this study, the majority (40.83 percent) of students live in an urban cluster, about 26 percent live in an urban defined area, about 12 percent live in a rural area less than 25 miles from an urbanized area and almost 21 percent live in a rural area over 25 miles from an urbanized area. The distribution of ACT scores is not heavily influenced by rurality (see Figure 14 in Appendix), and about 95 percent of students graduate within the 2019 cohort across all rural codes.

Reservation Status. Across the sample, the majority of students live off-reservation (93.70 percent), however there are notable differences between students who live on- and off-reservation. Students who attend school off-reservation have a mean ACT score (19.92) that is 3.70 points higher than students who attend school on-reservation (16.22) (see Figure 15 in Appendix). Almost 8 percent of students dropped out on-reservation while approximately 5 percent dropped out off-reservation. About 24 percent of on-reservation students experience mobility, while less than 15 percent of off-reservation students experience mobility. A Pearson's chi-squared test ( $<.001$ ) indicates a statistically significant relationship between school's reservation status and mobility. However, Cramer's V (0.062) indicates a very weak substantive relationship between the two variables. School location on- and off-reservation also is informed by school poverty where the mean IPR for schools on-reservation is 161.91 compared to schools off-reservation at a mean IPR value of 287.11 (see Figure 16 and Figure 17 in Appendix). Proportionally, there are opposing experiences of individual student poverty between on- and off-reservation schools as well. Of students attending schools on-reservation, 88.12 percent experience high poverty. Of students attending schools off-reservation, over 70 percent

experience low poverty. These patterns between academic success, opportunity factors, and school location crave further exploration and understanding.

Native Student Density. The variable for Native student density groups schools in one of four school types defined by the school's Native student population. If a school's student population is 0 to 24 percent Native (91.36 percent of students' experience in the sample) they are considered low density on one end of the spectrum, and 75 to 100 percent Native (5.08 percent) they are considered high density. Students at higher density schools present lower mean ACT scores ( $M = 15.91$ , see Figure 18 in Appendix), higher proportions of students experiencing mobility (36.67 percent), and higher dropout rates (6.93 percent), while students at lower density schools have higher mean ACT scores ( $M = 19.96$ , see Figure 18 in Appendix), lower proportions of students experiencing mobility (13.53 percent), and lower dropout rates (5.03 percent). These patterns between academic success, opportunity factors, and schools' student population also crave further exploration and understanding.

Title 1 Status. The variable for Title 1 status defines all schools in the sample and how they participate with Title 1 programs. About 72 percent of students in the sample attend a school that is either receiving target assistance or participating in a school-wide program. There do not appear to be major differences in the distribution of ACT scores by Title 1 status (see Figure 19 in Appendix), and across all status types 94 percent or higher graduated with the 2019 cohort. Mobility by Title 1 status does not present significant differences. In fact, across all status types, the proportion of students experiencing mobility is greater than 12 and less than 20 percent (only approximately an 8 percent difference across status types).

### Instrumentation Validity and Reliability

As noted previously, this study is a nonexperimental research design that involved analysis of longitudinal student-level and school-level data following a single cohort of Montana high school students. The population for this sample is all high school students in Montana during the 2018-2019 graduation cohort where 2018 would have been their Junior year of high school, and 2019 their graduating year. Because the sample generated was directly from AIM, the sample is representative and random. Random sampling protects against bias and allows some predictability of the sampling error (Agresti, 2018). The ways in which this sample is not representative or random exists in the schools and students not included in the sample. Only public Montana high schools are included, where private, homeschool, and other specialty institutions are not included. Additionally, only students who remained enrolled, graduated, or dropped out from a Montana public school were included in the sample. This is of particular importance when considering student mobility: student mobility which resulted in enrollment to a private institution, out of state institution, homeschool, or other special scenario<sup>4</sup> are not captured by the data collection.

Significant limitations exist for the way data is collected for a couple of specific elements. The data available to characterize and recognize race is one such example. There are five federally recognized categories for coding data on race (DOI, 2021). Federal codes generalize all tribal affiliations into a collective group limiting the complex community and individual identities represented in these conglomerate and collective student groupings.

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<sup>4</sup> Special scenarios may include enrollment to behavioral health specialty schools, correctional facilities, Indian bureau schools, the Montana School for the Deaf and Blind, or the Montana state prison.

Measuring student poverty has historically faced limitations defaulting to eligibility for free and reduced-price lunch (FRPL) as a proxy measure. Further, few students have their household incomes verified to confirm eligibility (NCES 2021b) disrupting the validity of the student-level indicator. In addition, using FRPL as a proxy measure is limited due to school-level participation. Some schools provide meals to all their students (NCES, 2021b). In such cases, FRPL data function as a school-level rather than a student-level poverty indicator. While utilization of the SIDE metric for Montana schools provides an improved, continuous measure for school-level poverty, IPRs at the student-level are currently unavailable due to unobtainability of student addresses in Montana. In this way, FRPL data remain the option available for considering student-level poverty.

Considering content validity, the ACT is an achievement test intended to measure an individual's proficiency in a particular knowledge or skill, where the test is standardized and the individual's performance is determined by comparing to the national group (Mills & Gay, 2019). While composite ACT score was utilized as the achievement measure rather than single content area scores, and GPA was avoided due to concern of inconsistent and subjective scoring methods, potential concerns persist regarding whether ACT is an accurate score of achievement and the ACT instrument's validity (Mills & Gay, 2019).

One delimitation of this study is to set boundaries around investigating only high school students for the most recent school years. The "achievement gap" is acknowledged for elementary, middle and high school students, where achievement is measured using both standardized test scores and graduation rates (OPI, 2022), but this study focuses on only high school students' ACT scores only for academic achievement. Another delimitation of this study

is the longitudinal scope of student data considered. While persisting educational inequality is evident between Montana students, this study sets boundaries around two school years (2017-2018 and 2018-2019) for the outcome variables. Lastly, as a quantitative designed study, boundaries are set around examining through set measures rather than aligning to experiential or narrative data. In this way, the Montana “achievement gap” is redefined, but unaccompanied by the perspectives of students and stakeholders. Qualitative effort to capture these perspectives of students is missing from this study, in this way little is known about what instigates mobility for students. This is of particular concern in regards to the Native student population where familial norms and kinship structures may influence the mobility of students between homes and schools (see Chapter 5).

### File Preparation

After the dataset was gathered from AIM including all variables outside of the school poverty measure, the dataset was aligned to data generated from BlindSIDE. The data generated from BlindSIDE was for 2019 including school name and location data, as well as an IPR value for each unique school. The AIM dataset and the BlindSIDE dataset were aligned in Excel by school code, which is a unique school identifier. After merging the IPR values, the dataset’s categorical variables were cleaned to function as binary and nominal variables using numeric coding (i.e. M/F coding to 0/1 coding for gender). The student poverty variable underwent some data manipulation to code as binary. The student poverty (FRPL) data was provided coding students as receiving free lunch (F), reduced price lunch (R), or N (not eligible for free or reduced price lunch). Students coded as N were transformed to 0 representing students with low

poverty. Students coded as F and R were grouped and all were replaced with 1 representing students with high poverty.

Missing Data. There were 918 students, or about 9.5 percent of the sample, missing an ACT composite score in the sample. Please see the Variables section above for the detailed reporting of missing data and how it was handled. In summary, multiple imputation (Rubin, 1987; 1996) was used rather than mean replacement as it significantly impacted the sample density (see Figure 2 in the Appendix). Listwise and pairwise deletion methods are also avoided as they tend to produce standard errors that are too large or too small, respectively (Van Buuren, 2018). Rather, multiple imputation is the procedure utilized in this study to handle missing ACT scores through 10 imputed datasets ensuring robustness in the results using the Predictive Mean Matching (PMM) method. Imputation was run for a maximum of 50 iterations and random seed set at 123 for reproducibility. All relevant variables were included in the imputation model, and after the imputation process results were pooled using Rubin's rules to combine estimates and standard errors. After multiple imputation, mean ACT decreased ( $M = 19.65$ ). The density plot of ACT after multiple imputation presents what is accepted as normal distribution in this study, see Figure 3 in the Appendix.

Outliers. Please see details in the School Poverty section of Independent Variables above for details. In summary, analysis of outliers across academic achievement (ACT composite score) and school poverty was conducted using three methods: (1) evaluation of interquartile range (IQR) values by defining outliers as 1.5 times the IQR above the third quartile and below the first quartile, (2) identifying a z-score threshold of a score greater than 3 or less than -3, and (3) utilizing a modified z-score as a robust method less sensitive to outliers than the standard z-

score by using the median and median absolute deviation (MAD). School poverty was the only element to present an outlier that would need further identification and handling. There was one school in the sample whose poverty metric presented an outlier. It is anticipated the IPR value was inflated due to the school's close proximity to downtown. Rather than remove the school, its school poverty value was replaced with the mean across the other three schools in that district ( $M = 324$ ). After handling this school as an outlier, the mean IPR value for the sample decreased ( $M = 279.22$ ) and the range naturally adjusted as well (98 to 412). The density plot for school poverty presents a fairly normal distribution (see Figure 4 in the Appendix).

### Data Analysis

In preparation for analysis, the complete and cleaned dataset was imported to R using Rstudio. All continuous variables were coded numeric and categorical variables were renamed and coded as factor variables. Descriptive statistics were generated for all variables and the scenario of missing ACT data was handled using multiple imputation. Exploratory data analysis utilized two-way contingency tables and matrix box chart visuals for examining relationships between categorical outcomes and categorical predictors, trends and normality of continuous variables, relationships between continuous and categorical variables using boxplot and aggregate functions to explore mean by categorical groups, linear correlations between continuous variables using scatter plot matrices, and the correlation of categorical variables using Pearson's chi squared test and Cramer's V. R packages utilized include plyr, psych, ggplot2, car, rcompanion, ggmosaic, multiwayvcov, lmtest, dplyr, e1071, mice, miceadds, margins, foreign, multilevel, MASS, tidyverse, nlme, misty, r2mlm, lme4, lmerTest, lattice, lavaan, interactions, and mediation. Articulation of results from exploratory data analysis and descriptive statistics

can be found in the Variables section above. The dataset is then used for the stages of analysis in this study: (1) saturated regression models examining the outcome measures by social locations and (2) robust Multilevel Modeling (MLM) to investigate the relationship of opportunity factors on academic achievement and academic completion by considering nesting in schools as a geographically informed context.

### Social Location Saturated Regression Models

The first stage of data analysis answers the first two research questions. First contrast coding, specifically effect coding, was utilized to better understand the unique relationship gender, race and student poverty had with the outcome variables. Next, by exploring social locations through a full set of gender, race and student poverty variables as well as all possible interactions between gender, race and student poverty, the models used to explore students' relationships to academic success (achievement and completion) are saturated models. While this analysis runs the risk of overfitting the data due to such saturation, the focus of these models is to better understand how distinct social locations intersect to portray unique experiences. Subjects in the sample report two genders, seven race categories, and fall into one of the two poverty defined groups. Therefore, there are  $2 \times 7 \times 2 = 28$  social locations or unique 'groups' conceptualized as distinct categories of experience in the saturated models. Replicating López and team's study (2018), estimates and marginal effects are reported where the reference group is white, low-poverty, females.

Saturated Linear Regression Model. Linear regression is the appropriate model for exploring, through intersectionality methodology aligned with QuantCrit, how the outcome measure of academic achievement changes when social locations change. Linear regression is

the appropriate statistical procedure because a linear relationship is used between explanatory variables, where an explanatory variable can be examined while controlling for the other variables within the model (Agresti, 2018) and the outcome variable is continuous. In this study, the variable for academic achievement (ACT composite scores) functions as a continuous variable. The following is the model building for the effect coding and saturated model:

Model a (effect coding) –  $ACT \sim \text{gender}$

Model b (effect coding) –  $ACT \sim \text{race}$

Model c (effect coding) –  $ACT \sim \text{student-level poverty}$

Model d (saturated model) –  $ACT \sim \text{gender} * \text{race} * \text{student-level poverty}$

This model specifically answers the first research question: Are there observable differences by academic achievement based on students' social location orientation (gender, race, class)?

Saturated Logistic Regression Model. Logistic regression is the appropriate model for exploring, through intersectionality methodology aligned with QuantCrit, how the outcome measure of academic completion changes when social locations change. Logistic regression is the appropriate statistical procedure because loglinear models describe the structure of association among a set of categorical outcome variables (Agresti, 2018) and in this study the outcome variable is categorical. In this study, the variable for academic completion functions as a nominal variable. The following is the model building for the effect coding and saturated model:

Model a (effect coding) –  $\text{Graduate} \sim \text{gender}$

Model b (effect coding) –  $\text{Graduate} \sim \text{race}$

Model c (effect coding) –  $\text{Graduate} \sim \text{student-level poverty}$

Model d (saturated model) – Graduate  $\sim$  gender \* race \* student-level poverty

This model specifically answers the second research question: Are there observable differences by academic completion based on students' social location orientation (gender, race, class)?

### Robust Multilevel Models Exploring Opportunity Factors

The second stage of data analysis answers the third and fourth research questions where academic success is defined as two separate outcome variables (academic achievement and academic completion). This stage of analysis drops investigation by social locations and instead utilizes the demographic characteristics as student-level control variables on a within-group sample of Native students. In this way, the independent variable for these models is student mobility. Two sets of control variables are utilized as well. Student level controls include gender, student-level poverty, and English Learner status. School level controls include reservation status, Native student density, Title 1 status, school rurality and school poverty. The robust models consider school-level differences through random intercepts.

This stage of analysis addresses the third and fourth research questions: How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic achievement (ACT scores, RQ3) and student academic completion (graduate/dropout; RQ4)? The within-school model (level-1) looks at the relationship between ACT achievement, as well as academic completion, and mobility. The between school model (level-2) where the coefficients of level-1 become the outcome, accounts for school level poverty, with the assumption that level-1 and level-2 errors are independent. While poverty accounts for some of the between school variation in the relationship between achievement and mobility,  $U_{0j}$  and  $U_{1j}$  account for the deviance remaining,

also considered the random effects. The fixed effects,  $Y_{00}$  and  $Y_{10}$ , provide the relationship between a predictor in the model and an outcome, or mobility, poverty and the outcome of achievement.

When estimating models, the coefficients, standard error, and significance levels are produced at both levels providing a level-1 and a level-2 estimate for the fixed and random effects on achievement/completion outcomes. In this way, estimated coefficients (fixed effects) and their standard errors for each predictor variable included in the model are provided, as well as the estimated variance components (random effects) for each level of analysis. The following are the equations for each model:

Level-1: Within school model

$$Y_{ij} = \beta_0 + \beta_{1j} \text{MOBILITY}_{ij} + r_{ij}$$

Level-2: Between school model

$$B_{0j} = Y_{00} + Y_{01} \text{POVERTY} + U_{0j}$$

$$B_{1j} = Y_{10} + Y_{11} \text{POVERTY} + U_{1j}$$

Combined Model:

$$Y_{ij} = Y_{00} + Y_{01} \text{POVERTY} + Y_{10} \text{MOBILITY} + Y_{11} \text{MOBILITY} * \text{POVERTY} + U_{0j} + U_{1j} \text{MOBILITY} + r_{ij}$$

MLM is the appropriate statistical procedure because a multilevel data structure considers one set of units is nested or clustered in another set of units. A relevant example is students nested within classrooms, which is considered an organizational example, allowing for examination of variation at multiple levels of the data. In this way, the study avoids underestimating standard error for between-cluster effects (increase of type one errors) as well as overestimating standard error for within-cluster effects (increase of type two errors). If a school-level regression analysis is utilized, the study would only look at the relationship between school means for achievement and for mobility. This study highlights there is within school variation in achievement and mobility, therefore considering spatiality.

Robust Linear MLM. This model specifically answers the third research question considering academic achievement as one method for measuring academic success. Linear MLM is utilized when the dependent variable is continuous, the data is hierarchically structured, there is a need to capture variability at multiple levels and there is need to model both the fixed and random effects (Snijders & Bosker, 2012). The models first examine the independent variable individually. Entering the independent variable before any controls provides an estimate of the relationship with the dependent variable (Frost, 2007; Lewis, 2007). This strategy also allows for an assessment of how the controls change the relationship between the independent and dependent variable. The block of models utilize random intercepts modeling where there is consideration for school-level differences. In this way, the following are the equations for building the model:

Model null: Academic Achievement (ACT) = (1 | school)

Model a: Academic Achievement (ACT) = Student Mobility + (1 | school)

Model b: Academic Achievement (ACT) = Student Mobility + Student Controls (1 | school)

Model c: Academic Achievement (ACT) = Student Mobility + Student Controls + School Controls (1 | school)

When estimating models for predicting achievement, the correlation coefficient and significance level reveal whether the relationship between explanatory factors are predictors of achievement. Using the standard error, a 95% confidence interval can be provided, and the adjusted r-squared value indicates the percent of achievement that can be examined by the explanatory variables.

Robust Logistic MLM. This model specifically answers the fourth research question considering academic completion as one method for measuring academic success. Logistic MLM is used when the dependent variable is binary, the data is hierarchically structured, there is a need to capture variability at multiple levels and there is need to model both the fixed and random effects (Snijders & Bosker, 2012). The models first examine the independent variable individually. Entering the independent variable before any controls provides an estimate of the relationship with the dependent variable (Frost, 2007; Lewis, 2007). This strategy also allows for an assessment of how the controls change the relationship between the independent and dependent variable. The block of models utilize random intercepts modeling where there is consideration for school-level differences. In this way, the following are the equations for building the model:

Model null: Academic Completion (graduate/dropout) = (1 | school)

Model a: Academic Completion (graduate/dropout) = Student Mobility + (1 | school)

Model b: Academic Completion (graduate/dropout) = Student Mobility + Student Controls (1 | school)

Model c: Academic Completion (graduate/dropout) = Student Mobility + Student Controls + School Controls (1 | school)

When estimating models for predicting completion, the correlation coefficients, standard errors, as well as the odds ratios and associated confidence intervals reveal whether the relationship between explanatory factors are predictors of a student's end status. Reporting AIC and residual deviance also assess the validity of the model and goodness of fit, all important indicators for model selection and interpreting results.

### Assumptions

Assumptions diagnostics will be addressed across all three stages of the study. For the saturated models, diagnostics to test the assumptions for linear regression will be conducted. These tests include the variance inflation factor to test for no multicollinearity, a Durbin Watson test for no autocorrelation, and a Cook's distance for influential observations (Kutner, 2005). Visualizations will also be created to test for the normality of residuals, correct functional form, and outliers. In addition, diagnostics to test the assumptions for logistic regression will also be conducted. These tests include the variance inflation factor to test for no multicollinearity, test for no autocorrelation, test for influential observations, and a test for linearity of the logit. Analysis will also be provided of the ROC curve visualization and AUC value.

The second phase of this project utilizes MLM and therefore assumptions diagnostics will be addressed concerning the hierarchical structure of the data where the clusters (i.e. schools) are assumed to be independent of one another. MLM carries particular concern over residuals, or the difference between what is observed and what is estimated. In this way, level-1 predictors are assumed to be independent of the level-1 residuals, level-2 predictors are assumed to be independent of the level-2 residuals, and level-1 and level-2 errors are assumed to be independent of each other. Appropriate checks include testing for linearity, the independence of observations, the normality of residuals, homoscedasticity, multicollinearity, and variability at each level of analysis by checking level-1 and level-2 residuals. Level-1 assumption tests include examining normality of residuals through use of visuals such as histogram and Q-Q plots, as well as tests for homoscedasticity and non-linearity. Level-2 assumptions tests also include examining

normality of residuals, but also checking linearity by plotting level-2 residuals against the level-2 predictor. Lastly, influential level-2 units are examined using Mahalanobis distance.

Across analysis, the intention will be to further consider diagnostic measures by reporting both R-squared and adjusted R-squared values to provide a more comprehensive assessment of the models' fit. The R-squared value, or Coefficient of Determination, measures the proportion of variance in the outcome that is explained by the predictors in the model, where a higher R-squared value indicates a better fit of the model. The adjusted R-squared value is also provided because it adjusts for the number of predictor variables in the model, penalizing models that may overfit the data. This is of particular interest for the first stage of analysis where the models are intentionally saturated. While the adjusted R-squared generates a more conservative estimate of model fit, it is an important component for transparency in the study analysis. Lastly, as noted in the Data Analysis section, model fit indices such as AIC for the logistic regression models, or residual plots and significance levels for linear regression models, will also be provided.

### Study Reliability and Validity

Internal validity largely depends on the rigor and consistency of a study's procedures to establish a trustworthy causal relationship (Mills & Gay, 2019). One effort taken to address extreme values is through thorough exploratory data analysis prior to model analysis, as well as thorough assumptions tests for each of the statistical strategies utilized. Confounding variables with unanticipated effect on the dependent variable threaten the internal validity of a study by an increase in variance and potential for bias. Efforts include the elimination of bias through a random sample, exploring descriptive statistics, and establishing control variables for each best fitting model. Exploratory data analysis is provided in the Variables section above.

External validity refers to the generalizability of the study's findings to the population (Mills & Gay, 2019). With access to AIM, the sample collects from a comprehensive database for a generalizable sample. Students are not removed from the sample unless they did not remain eligible observations based on the parameters investigated such as moving to a private institution. Missing data for both ACT scores and mobility was supplemented using the mean for the entire sample. Insight is made as transparent as possible, including descriptive statistics of the missing data and sensitivity tests for the missing data's influence on the outputs.

It is important to consider the reliability of some variables' consistency in measurement over time. Pre-COVID data (2015–2019) was intentionally used for this study to avoid the significant disruptions the COVID-19 pandemic had on educational data, including student mobility patterns. The pandemic drastically altered students' movement between homes, neighborhoods, and schools, and these changes could impact the consistency of mobility data if collected during or after the pandemic. Additionally, the results of this study do not capture the effects of COVID-19 on outcome measures, and it is possible that any re-bounding effects post-COVID could differ significantly from the pre-pandemic trends observed here. Future studies should consider the pandemic's impact when interpreting findings from more recent data.

Lastly, the goal of this study is to utilize quantitative analysis aligned to QuantCrit methodology, concerning spatially informed context using CRSA methodology, to dismantle ignorant policy and reporting in Montana that defines a racial binary about the “achievement gap” between Native and non-Native students. The outcome variables mimic the focus of this “achievement gap” reporting by examining impact on academic achievement (ACT scores) and academic completion (graduation/dropout). In addition though, it also considers intersectionality

by social locations and the opportunity factors of student mobility, student poverty and school poverty to better inform critical and spatial analysis of academic access across students' experience in Montana. It is imperative to be concerned with what is not captured, neglected, or potentially misinterpreted through the results of this study. In particular, student mobility is utilized to better understand relationships to academic success. However, mobility is also only captured in the experience of enrolling to a new school, but neglects to capture any relative perspective data as to why the student is enrolling in a new school. Great caution should be taken in interpreting results. For example, if the findings of this study align to the existing literature that students in Montana from high poverty, minority racial groups, and higher rates of mobility have lower scores on the ACT and higher dropout rates, it cannot also be assumed the reasons for school mobility were negative. Consideration for the strengths associated with student mobility (see Chapter 5) are not adequately addressed in this study deterring from construct validity.

### Chapter Summary

This chapter provided an overview of the methodology used in this study. The utilization of social locations in the saturated models aligns with intersectionality methodology as part of the emerging field of QuantCrit. Particular attention to spatially informed variables such as school-level poverty, school reservation status, and Native student density align to efforts of quantitative spatial analysis as part of CRSA methodology to weave realities of unjust school spaces into standard Montana “achievement gap” reporting. Descriptions of the research design, sample, variables and data collection were provided. The methods of analysis appropriately examine the outcomes of academic achievement and completion where linear regression is applied to continuous outcomes, and logistic regression to categorical outcomes. MLM is also

utilized appropriately to consider the nesting of students in schools. Diagnostic analysis used to assess the models are articulated. Additionally, outcomes and visuals of these diagnostic analyses will be provided. The following chapter presents the results of these analyses.

## CHAPTER FOUR

## RESULTS

The purpose of this study is to better define and understand the disparity in standard metrics for academic success between Native and non-Native students in Montana, namely academic achievement (standardized assessment scores) and academic completion (graduate vs. drop out). As part of an emerging field of QuantCrit, this study first seeks to utilize intersectionality within quantitative methods to better understand the relational impact of race-gender-class gaps on academic success in K-12 Montana education. Policy around the “achievement gap” in Montana narrowly defines the gaps between Native and non-Native students only. Replicating López and team’s (2018) work, investigation through social locations provides statistical background to better understand students’ unique orientation to success, not just race. Second, this study seeks to redefine “achievement gap” policy and research by including opportunity factors (i.e. student poverty, student mobility, and school poverty) and investigating their impact through models aligned to existing policy’s outcome metrics of academic achievement and academic completion.

The research questions were addressed using multiple analytical strategies. The first step was to use effect coding for race, gender, and student poverty, which are the proxy variables for social locations. Effect coding was used to estimate the relationship of each social location with the outcome measures. Effect coding was used to get a more direct interpretation of the main effect for the different categories of each variable (race, gender, and student poverty). Closely following effect coding analysis, saturated linear and logistic regression analyses were conducted by exploring social locations through a full set of gender, race and student poverty variables as

well as all possible interactions between gender, race and student poverty. In this way, these models utilize 28 social locations or unique “groups” conceptualized as distinct categories of experience in the saturated models, replicating López and team’s study (2018), where the reference group is white, low-poverty, females. The linear saturated model where ACT composite scores (academic achievement) function as the outcome answer the first research question which asks, “Are there observable differences by academic achievement based on students’ social location orientation (gender, race, class)?” The logistic saturated model where end status of graduate or dropout (academic completion) functions as the outcome answer the second research question which asks, “Are there observable differences by academic completion based on students’ social location orientation (gender, race, class)?”

The third research question asks, “How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students’ academic achievement,” where academic achievement is defined by Junior year ACT composite scores. To answer this research question, robust linear Multilevel Modeling is utilized where student-level opportunity factors of student mobility and student poverty are the independent variables in addition to school-level factors such as school poverty, and academic achievement as the outcome variable. Similarly, robust logistic Multilevel Modeling is utilized to answer the fourth research question, which asks, “How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students’ academic completion,” where academic completion is defined by the binary outcome of cohort graduation or dropout. Multilevel Modeling it utilized to examine the within-school model (level-1) which looks at the relationship between academic

achievement/academic completion, mobility, and student characteristics, as well as between the school model (level-2) which accounts for school-level poverty. The set of student-level controls include student poverty and student gender. The set of school-level controls include school poverty, rurality, reservation status, Native student density, and title 1 status. The use of MLM to answer the final two research questions appropriately considers the nesting of students in schools as an important element to understanding the spatially influenced opportunity factors students in Montana face to academic success.

### Analytic Approach and Analysis Results

Descriptive statistics were run on the sample and results were covered in the Variables section of Chapter Three. A brief overview is provided in Chapter Four which are important to the interpretation of results. The study's sample is comprised of 9,621 students from the 2019 cohort where their ACT composite score is gathered from their Junior year and mobility across all years of high school. The majority of the sample identifies as white (82.65 percent) and the second largest category by race is students who identify as Native (American Indian/Alaskan Native and Multiracial) at 8.55 percent. Most students successfully graduate within their cohort (94.84 percent) and only 496 students dropped out. The mean school poverty across the sample of students is 279.20 and only approximately 33 percent of students experience high levels of individual poverty. The proportions of students attending schools by location parallel in expected ways where about 94 percent of students attend schools off-reservation and with low Native student density, while about 6 percent of students attend schools on-reservation with high Native student density. The mean ACT score across the sample is 19.65 which is 2.35 points below a

college readiness score. The norm in this sample is to not experience mobility, or to attend the same high school all four years. Almost 85 percent of the sample did not experience mobility.

There are some notable characteristics of the independent variables when considering descriptive statistics. First, students who experience high poverty appear to have lower academic achievement rates and have higher mobility tendencies than their low-poverty peers. The mean ACT score for students in high poverty ( $M = 17.86$ ) is almost 3 (three) points lower than the mean ACT score for students in low poverty ( $M = 20.62$ ). It is important to note that students' mobility experience may have occurred after their participation on the ACT test as these scores were collected their Junior year (2018) and mobility was captured across all four years of high school. While this criteria violates the time order of the x and y variables, this study seeks to align to existing mobility research which argues the importance of measuring mobility across the academic experience when examining various performance outcomes such as graduation and achievement (Engec, 2006; Rumberger & Larson, 1998; Swanson & Schneider, 1999). Almost 25 percent of high poverty students experience mobility, while only 10.36 percent of low poverty students experience mobility. Considering poverty status impact on academic completion, 53.43 percent of students who dropped out were high poverty. Second, mobility not only seems to be more prevalent among high poverty students, but also based on students' racial categories. While only about 13 percent of white students experience mobility, approximately 32 percent of American Indian/Alaskan Native (AIAN) and 24 percent of Black students experience mobility. Considering an aspect of students' location, on-reservation (23.60 percent) students—which have higher densities of Native students—experience mobility more than off-reservation (14.52 percent) students. Also, the mean ACT composite score for students experiencing mobility is

17.49 while students not experiencing mobility is 20.04. Lastly, school-level poverty also may impact students' experience and success. Mobility seems to present a relationship to school poverty as students who experienced mobility attend schools with a mean IPR value of 265.00 while students who did not experience mobility attend schools with a mean IPR value of 281.75. School location on- and off-reservation is informed by school poverty where the mean IPR for schools on-reservation is 161.91 compared to schools off-reservation at a mean IPR value of 287.11. Considering academic success, there may be relationships between school poverty and academic achievement and completion. Examining ACT and school poverty, there appears to be a positive linear relationship where students with higher ACT scores are also more likely to attend a school with a higher IPR value (see Figure 5 in Appendix). Considering end status and school poverty, students who dropout attend schools with a slightly lower IPR value (275.78) compared to their peers who graduate (279.41).

### Model Building

Aside from the contrast coding and saturated models, the independent variable (student mobility) was entered individually for model building. Entering the independent variables before any controls provides an estimate of the relationship with the dependent variable (Frost, 2007; Lewis, 2007). This strategy also allows for an assessment of how the controls change the relationship between the independent and dependent variable. In addition, it highlights the changes in R-squared and the efficiency of the models, providing nuance to the relationships. The control variables were added in two sets after the independent variable: first the student-level controls and second the school-level controls.

### Social Location Saturated Regression Models Results

The first stage of data analysis answers the first two research questions. First contrast coding, specifically effect coding, was utilized to better understand the unique relationship gender, race and student poverty had with the outcome variables. Next, by exploring social locations through a full set of gender, race and student poverty variables, as well as all possible interactions between gender, race and student poverty, the models used to explore students' relationships to academic success (achievement and completion) are saturated models. Replicating López and team's study (2018), marginal effects are reported where the reference group is white, low-poverty, females.

Contrast coding, specifically effect coding (Daly, Dekker & Hess, 2016) compares each level of the race, gender and class variables to the grand mean. Within effect coding, a single reference group is not used, rather, all groups are compared to the grand mean. In this way, understanding of these variables' relationship to the group mean is established prior to analyzing by intersecting and distinct social locations in the saturated models, aiding in answering the first two research questions. Contrast coding across the variables for race, gender and poverty are provided for when  $y$  = academic achievement (ACT composite score) and for when  $y$  = academic completion (graduate/dropout). The contrast coding results provide comparisons to grand mean to better understand baseline relationships. In alignment to the understanding that there are a range of opportunity factors impacting students' academic success, the effect coding results suggest there are other factors which may also contribute to differences in ACT scores and graduation outcomes.

Overall, the examination of social locations through saturated models revealed little statistically conclusive impacts of the intersections of race, gender and student poverty. Similar to effect coding, the saturated models did reveal the significant impact student poverty has on academic success. In particular, high poverty students have significantly lower scores on the ACT and are less likely to graduate. Race also presents itself as a factor to consider as AIAN, Black, and Hispanic students all had significantly lower ACT scores. While race had less of an impact on graduation, AIAN students did present 62 percent lower odds of graduating. While the interactions—or the intersections of social locations—suggest gender, race and student poverty largely operate independently of one another, the interactions between AIAN and high poverty, as well as male and high poverty, students are statistically significant and should be considered with care in the context of spatial context in Montana such as on- and off- reservation differences (see Literature Review).

#### RQ 1: Social Locations and Academic Achievement

See table 8 below for the results of effect coding as well as the results of the saturated linear model. The following is the model building for the effect coding and saturated model:

Model a (effect coding) – ACT ~ gender

Model b (effect coding) – ACT ~ race

Model c (effect coding) – ACT ~ student-level poverty

Model d (saturated model) – ACT ~ gender \* race \* student-level poverty

Across gender, race and student-level poverty in effect coding analysis of academic achievement (ACT performance), analysis showed the amount of variance explained by these models is relatively modest (adjusted R-squared 0.0042-0.0862), despite their statistical significance. The importance of analyzing the three variables of social location independently through effect

coding allows for consideration of the unique effects of each on ACT scores prior to running the saturated models which explore the intersections of gender, race and student-level poverty. Considering ACT scores, gender had the smallest impact and student-level poverty had the largest. The effect of gender on academic achievement (ACT scores) using effect coding revealed a statistically significant effect. There is a significant difference on ACT between male ( $SE = -.05, p < .001$ ) and female ( $SE = 0.05, p < .001$ ) students, with males having a slightly higher ACT score ( $\beta = 20.04$ ) compared to females ( $\beta = 19.71$ ). The intercept represents the average ACT score for the reference group (female) with an estimate of 19.71. Male students score 0.33 points higher on the ACT compared to females. The model explains a small amount of the variance in academic achievement where R-squared is a value of 0.0043.

The effect of race on academic achievement indicates several statistically significant differences between racial groups. The model's intercept represents the average ACT score for the reference group (white students) with an estimate of 18.60 ( $SE = 0.19, p < .001$ ). In addition, AIAN students had significantly lower ACT scores. These students were 2.74 points lower compared to the average ( $SE = 0.25, p < .001$ ). Black students also had lower ACT scores compared to the average by 1.98 points ( $SE = 0.48, p < .001$ ). In comparison, Asian students had significantly higher ACT scores by 3.08 points ( $SE = 0.55, p < .001$ ). The model explained 6.39 percent (R-squared = 0.0639) of the variance in ACT scores.

Student-level poverty indicated the greatest effect on ACT scores in the effect coding analysis. The intercept represents the average ACT score for the reference group (low poverty) with an estimate of 19.12 ( $SE = 0.05, p < .001$ ). Students from high poverty backgrounds had significantly lower ACT scores by 1.58 points compared to their peers from low poverty ( $SE =$

0.05,  $p < .001$ ). The model explained 8.63 percent (R-squared = 0.0863) of the variance in ACT scores. Table 8 captures the coefficients and directional difference from the mean for the gender, race and student poverty variables in effect coding.

The saturated linear regression model is statistically significant overall ( $F(27, 8675) = 43.62, p < .001$ ) in predicting students' academic achievement (ACT composite scores) based on the interactions of gender, race, and student poverty. The model explains approximately 11.68 percent of the variance in ACT scores (Adjusted R-squared = 0.1168). The reference group is low poverty, white, females and their average ACT score is 21.16. Males have a statistically significant lower ACT score compared to females by approximately 0.66 points ( $\beta = -0.6615, p < .001$ ). It is important to note that in effect coding, the result for males was the opposite where they scored higher on the ACT than female students. In the saturated linear model, AIAN students score on average 1.93 points lower than white students ( $\beta = -1.92672, p < .001$ ), Black students score 4.10 points lower ( $\beta = -4.09740, p < .001$ ), and Hispanic students score 1.92 points lower ( $\beta = -1.92367, p < .001$ ). Asian, Multiracial and Native Hawaiian/Pacific Islander (NHPI) did not have a statistically significant difference in their ACT scores. And, students from high poverty backgrounds score on average 2.49 points lower than their low-poverty peers ( $\beta = -2.49174, p < .001$ ). Table 8 captures the results of the saturated linear regression model exploring the interactions of gender, race and student poverty on academic achievement.

Table 8. Linear Regression Model Estimates for Effect Coding and Saturated Model

	<i>Model a</i>	<i>Model b</i>	<i>Model c</i>	<i>Model d</i>
<i>Intercept</i>	—	—	—	21.16***
<i>Gender</i>				
<i>Intercept (female)</i>	19.71***	—	—	—
<i>Male</i>	0.33***	—	—	-0.66***
<i>Race</i>				
<i>Intercept (white)</i>	—	18.60***	—	—
<i>AIAN</i>	—	-2.74***	—	-1.93**
<i>Asian</i>	—	3.08***	—	1.24
<i>Black</i>	—	-1.98	—	-4.10***
<i>Hispanic</i>	—	-0.41	—	-1.92***
<i>Multiracial</i>	—	0.39	—	-0.53
<i>NHPI</i>	—	0.07	—	1.68
<i>Student-Level Poverty</i>				
<i>Intercept (low poverty)</i>	—	—	19.12***	—
<i>High poverty</i>	—	—	-1.58***	-2.49***

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

In examining the interactions in the saturated linear model, this study replicates the work of López and team (2018) by reporting the marginal effects (see Table 9 below). In addition to interpretability, the focus on marginal effects is used in the saturated models for simplification: Marginal effects summarize the overall effect, simplifying the heavy use of interaction terms in this model. None of the three-way interactions between gender, race, and student poverty, or the full expressions of intersecting social locations, are statistically significant ( $p < .1$ ). There are two interactions to consider: First, the interaction between being male and from a high poverty background is significant ( $-0.68, p = .02$ ). Second, the interaction between high poverty and AIAN students shows a strong negative interaction effect ( $-3.49, p < .001$ ), indicating a compounded disadvantage for AIAN students in high poverty. AIAN students in high poverty conditions have lower ACT scores than AIAN students in low poverty conditions, with a more pronounced difference compared to their white peers. It is also worth noting the interaction

between NHPI and high poverty students presents similar effect (-3.83) however this interaction is not quite significant ( $p = 0.16$ ).

Overall, the saturated model indicates that gender, race and student poverty have significant impacts on academic achievement, however the lack of significant three-way interaction effects perhaps suggests that these factors operate relatively independently of one another. The social location of AIAN-high poverty students as well as male-high poverty students are the unique exceptions. Table 9 presents the marginal effects for the interactions in the saturated linear model for academic achievement. Examining the marginal effects can be particularly beneficial when considering interaction terms as it provides insight to the relationships between predictors and outcome as other predictors change. For example, in the analysis of social locations on academic achievement examining the marginal effects of race at different levels of poverty can illuminate how ACT scores vary for individuals of different race and poverty experiences.

Table 9. Saturated Linear Regression Model Marginal Effects

<i>Academic Achievement</i>		<i>M = 19.71</i>		
<i>Variable</i>	<i>Marginal Effect</i>	<i>Std. Error</i>	<i>p-value</i>	
<b>Gender</b>				
<i>Male</i>	-0.64	0.10	***	
<b>Race</b>				
<i>AIAN</i>	-2.44	0.29	***	
<i>Asian</i>	1.29	0.64	0.04	
<i>Black</i>	-3.25	0.55	***	
<i>Hispanic</i>	-1.48	0.28	***	
<i>Multiracial</i>	-0.75	0.32	0.02	
<i>NHPI</i>	-0.55	1.02	0.59	
<b>Student-level Poverty</b>				
<i>High poverty</i>	-2.56	0.12	***	
<b>Gender x Race</b>				
<i>Male x AIAN</i>	-1.06	0.84	0.21	
<i>Male x Asian</i>	-0.49	1.36	0.72	
<i>Male x Black</i>	-0.18	1.48	0.90	
<i>Male x Hispanic</i>	0.26	0.73	0.72	
<i>Male x Multiracial</i>	-1.13	0.83	0.17	
<i>Male x NHPI</i>	-3.83	2.71	0.16	
<b>Gender x Student Poverty</b>				
<i>Male x High Poverty</i>	-0.68	0.28	*	
<b>Race x Student Poverty</b>				
<i>AIAN x High Poverty</i>	-3.49	0.92	***	
<i>Asian x High Poverty</i>	1.45	2.01	0.47	
<i>Black x High Poverty</i>	-1.11	1.93	0.57	
<i>Hispanic x High Poverty</i>	-1.15	0.90	0.20	
<i>Multiracial x High Poverty</i>	-0.75	1.11	0.50	
<i>NHPI x High Poverty</i>	-2.24	3.27	0.49	
<b>Gender x Race x Poverty</b>				
<i>Male x AIAN x High Poverty</i>	0.05	1.29	0.97	
<i>Male x Asian x High Poverty</i>	-1.11	3.42	0.75	
<i>Male x Black x High Poverty</i>	-2.30	2.55	0.37	
<i>Male x Hispanic x High Poverty</i>	-1.41	1.31	0.28	
<i>Male x Multiracial x High Poverty</i>	-0.54	1.53	0.72	
<i>Male x NHPI x High Poverty</i>	-0.03	4.72	0.99	

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

## RQ 2: Social Locations and Academic Completion

See table 10 below for the results of effect coding as well as the results of the saturated logistic model. The following is the model building for the effect coding and saturated model:

Model a (effect coding) – Graduate ~ gender

Model b (effect coding) – Graduate ~ race

Model c (effect coding) – Graduate ~ student-level poverty

Model d (saturated model) – Graduate ~ gender \* race \* student-level poverty

Across gender, race and student-level poverty in effect coding analysis of academic completion, analysis showed, like academic achievement, that significant relationships exist. This analysis specifically found that male, AIAN, and high-poverty students warrant careful consideration, as they are less likely to graduate compared to their white, female, low-poverty peers. Effect coding for academic completion (graduate/dropout) utilizes logistic regression where the dependent variable is binary. The model estimates the log-odds of the outcome occurring (i.e. graduating from high school). Effect coding for academic achievement is able to compare to the grand mean of ACT scores because this outcome variable is continuous. For academic completion however, effect coding compares to the log-odds of graduating for the overall mean of all groups and the coefficients represent the difference in log-odds between each group and the overall. In this way, the results of effect coding for academic completion are transformed by exponentiating the coefficients to be interpreted as odds ratios, providing a more intuitive understanding of the effects for gender, race and student poverty.

A binary logistic regression was used to explore the effect of gender on academic completion. The effect of gender on academic completion (graduate/dropout) using effect coding revealed a statistically significant effect on graduation ( $\beta = 0.95$ ,  $SE = 0.048$ ,  $p < .001$ ). The

positive coefficient for males ( $\beta = 0.283$ ,  $SE = 0.048$ ,  $p < .001$ ). indicates that being male is associated with higher odds of graduating compared to being female. The odds ratio for gender is approximately 1.33, or in other words, males are about 1.33 times more likely to graduate than females. Similar to the findings in the linear saturated model, considering gender in isolation produces positive effect for males, however this is reversed when other factors are included and males in all other models of this study are less likely to graduate compared to their female peers. The model's AIC was 3,875.20 with a residual deviance of 3,871.2 on 9,619 degrees of freedom.

The logistic regression model analyzing the effect of race on academic completion revealed that race had a significant impact. The intercept represents the log odds of graduating for the reference group (white students), where the odds ratio for white students graduating is 14.31, indicating they are significantly more likely to graduate than not. AIAN students however ( $\beta = -0.459$ ,  $SE = 0.189$ ,  $p = 0.015$ ) are significantly less likely to graduate compared to their white peers, and further, the odds ratio of 0.63 suggests AIAN students are about 37 percent less likely to graduate. Similarly, the odds ratio (0.61) for Black students suggests they may be about 39 percent less likely to graduate compared to their white peers, though the effect is not statistically significant ( $p = 0.13$ ). In comparison, Asian students may be 2.45 times more likely to graduate ( $\beta = 0.895$ ,  $SE = 0.627$ ) compared to their white peers, though the effect is not significant ( $p = 0.15$ ) and therefore this finding is not statistically conclusive. The model's AIC was 3,870.1 with a residual deviance of 3,856.1 on 9,614 degrees of freedom.

Lastly, the effect of student-level poverty on academic completion was also considered in the effect coding analysis using logistic regression. The results indicate that student-level poverty has a statistically significant effect on end status ( $\beta = 0.444$ ,  $SE = 0.046$ ,  $p < .001$ ). The positive

estimate suggests that students from low poverty are more likely to graduate compared to their peers from high poverty. The odds ratio is 1.56, indicating that students from low poverty are 1.56 times more likely to graduate compared to their peers from high poverty. The model's AIC was 3,820.6, and it had a residual deviance of 3,816.6 on 9,619 degrees of freedom. Table 10 captures the coefficients for the gender, race and student poverty variables in effect coding.

The saturated logistic regression model examines the likelihood of graduating based on the interactions between gender, race and student poverty, or in other words, based on the previously defined social locations. Small sample sizes for Asian and NHPI students prompted some instability in the model. Separation was handled in the data by utilizing Firth's Penalized Likelihood through the `logistf` package. In scenarios such as small sample sizes standard maximum likelihood estimates may be biased causing large variability in the estimates as observed in high standard errors. Prior to use of Firth's Penalized Likelihood, high standard errors were observed of both Asian ( $SE = 430.97$ ) and NHPI ( $SE = 979.61$ ) students. Firth's method is particularly useful for addressing separation issues and reducing bias in logistic regression models, especially in scenarios of small sample sizes (Firth, 1993).

The odds of graduating for the reference group of low-poverty, white females ( $\beta = 3.63$ ,  $SE = 0.12$ ,  $p < .001$ ) are extremely high, where these students are about 37.55 times more likely to graduate than their peers. Males have approximately 36 percent lower odds of graduating compared to females ( $\beta = -0.45$ ,  $SE = 0.15$ ,  $p < .001$ ). AIAN students have 62 percent lower odds of graduating, where the effect is marginally statistically significant ( $\beta = -0.96$ ,  $SE = 0.50$ ,  $p = 0.10$ ). Multiracial students are 0.31 times less likely to graduate ( $\beta = -1.18$ ,  $SE = 0.46$ ,  $p < 0.05$ ). Asian students have high odds, where these students are 1.68 times the odds of graduating.

However, the effect is not statistically significant. Students from high poverty backgrounds have 53 percent lower odds of graduating ( $\beta = -0.74$ ,  $SE = 0.18$ ,  $p < .001$ ). Table 10 provides the estimates of the saturated model for gender, race and student poverty.

Table 10. Logistic Regression Model Estimates for Effect Coding and Saturated Model

	<i>Model a</i>	<i>Model b</i>	<i>Model c</i>	<i>Model d</i>
<i>Intercept</i>	—	—	—	3.36***
<i>Gender</i>				
<i>Intercept (female)</i>	2.95***	—	—	—
<i>Male</i>	0.28***	—	—	-0.45**
<i>Race</i>				
<i>Intercept (white)</i>	—	2.66***	—	—
<i>AIAN</i>	—	-0.46**	—	-0.96
<i>Asian</i>	—	0.89	—	0.52
<i>Black</i>	—	-0.50	—	-1.17
<i>Hispanic</i>	—	-0.16	—	-0.04
<i>Multiracial</i>	—	-0.09	—	-1.18*
<i>NHPI</i>	—	-0.10	—	-1.06
<i>Student-Level Poverty</i>				
<i>Intercept (low poverty)</i>	—	—	2.85***	—
<i>High poverty</i>	—	—	-0.44***	-0.74***

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

Similar to the examination of interactions in the saturated linear model, the interactions of the saturated logistic model replicate the work of López and team (2018) by reporting the marginal effects (see Table 11 below). Gender and high-poverty status independently show significant negative effects and AIAN students experience significant negative marginal effects, similar to the results for academic achievement (ACT scores). Males have a marginal effect of -0.03 ( $p < .001$ ), indicating a statistically significant negative effect. Similarly, high poverty students show a significant negative effect of -0.04 ( $p < .001$ ). A negative effect of -0.04 with a p-value of 0.02 ( $p < .05$ ) indicates a significant negative association for AIAN students. Across the remaining racial student groups, only Hispanic students show a borderline significant effect with a p-value of 0.06. Interactions between gender, race and poverty do not show strong

statistical significance. The exception being the significant ( $p < .05$ ) negative effect (-1.54) between male and Hispanic indicating a combined negative impact for males of Hispanic background, as well as the effect between male and high poverty. The interaction between being male and high poverty has a significant negative effect of -0.66 ( $p < .05$ ). None of the three-way interactions are significant. All the p-values are above 0.20 suggesting no substantial combined effects of gender, race, and poverty status. Table 11 provides the marginal effects of the saturated logistic model interactions.

Table 11. Saturated Logistic Regression Model Marginal Effects

<i>Academic Completion</i>		<i>Graduated = 9,125 (94.85%)</i>		
<i>Variable</i>	<i>Marginal Effect</i>	<i>Std. Error</i>	<i>p-value</i>	
<b><i>Gender</i></b>				
<i>Male</i>	-0.03	0.004	***	
<b><i>Race</i></b>				
<i>AIAN</i>	-0.04	0.02	*	
<i>Asian</i>	0.02	0.02	0.25	
<i>Black</i>	-0.05	0.03	0.13	
<i>Hispanic</i>	-0.03	0.01	0.06	
<i>Multiracial</i>	-0.02	0.02	0.17	
<i>NHPI</i>	-0.02	0.05	0.68	
<b><i>Student-level Poverty</i></b>				
<i>High poverty</i>	-0.04	-0.01	***	
<b><i>Gender x Race</i></b>				
<i>Male x AIAN</i>	-0.34	0.67	0.62	
<i>Male x Asian</i>	-1.86	1.59	0.24	
<i>Male x Black</i>	-0.55	1.05	0.60	
<i>Male x Hispanic</i>	-1.54	0.74	*	
<i>Male x Multiracial</i>	0.41	0.69	0.55	
<i>Male x NHPI</i>	-1.10	1.74	0.53	
<b><i>Gender x Student Poverty</i></b>				
<i>Male x High Poverty</i>	-0.66	0.27	*	
<b><i>Race x Student Poverty</i></b>				
<i>AIAN x High Poverty</i>	-0.49	0.75	0.51	
<i>Asian x High Poverty</i>	0.16	2.49	0.95	
<i>Black x High Poverty</i>	1.05	1.88	0.58	
<i>Hispanic x High Poverty</i>	-0.07	1.03	0.95	
<i>Multiracial x High Poverty</i>	-0.48	0.83	0.56	
<i>NHPI x High Poverty</i>	-1.15	2.27	0.61	
<b><i>Gender x Race x Poverty</i></b>				
<i>Male x AIAN x High Poverty</i>	-0.48	1.01	0.64	
<i>Male x Asian x High Poverty</i>	-0.65	3.06	0.83	
<i>Male x Black x High Poverty</i>	-2.69	2.12	0.20	
<i>Male x Hispanic x High Poverty</i>	-0.83	1.21	0.49	
<i>Male x Multiracial x High Poverty</i>	-0.20	1.19	0.87	
<i>Male x NHPI x High Poverty</i>	0.83	3.01	0.78	

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

### Summary of Saturated Models

Across examination of students' race, gender and poverty through contrasting coding and saturated models, aspects of students' social locations impact academic success. Through contrast coding, AIAN and high poverty students have lower scores on the ACT and are less likely to graduate compared to their peers. In examining the intersections of social locations in the saturated models, particular attention is drawn to lower ACT scores among high-poverty males and AIAN males, as well as the decreased likelihood of graduation for high-poverty males compared to their peers. While the saturated logistic model did present that Hispanic males may also have lower likelihoods of graduating, this study makes difficult decisions in alignment to policy and literature of how to focus analysis to answer the third and fourth research questions. Montana policy focuses on the "achievement gap" between Native and non-Native students. Analysis using contrast coding and saturated models to examine the impact of intersecting social locations on academic success consistently reveals significant differences for AIAN students. Therefore, the remaining analyses in this study focus exclusively on a within-group sample of AIAN students.

The preliminary findings of the contrast coding and saturated models seem to reveal specific needs and contexts of AIAN students different from other racial groups in Montana—particularly white students. By focusing exclusively on AIAN students in remaining analyses, this study hopes to avoid aggregation bias where the unique challenges of AIAN students become invisible in the broader sample. In addition, a within-group sample increases the statistical power to highlight differences or trends specific to AIAN students, ultimately providing more robust and reliable results. History and literature address long-standing systemic challenges faced by Native peoples. Existing data and policy declare a need to better understand

the unique experience of Native students toward academic success. The early results of this study seem to reveal consistent need to better understand the differences for AIAN students in relationship to academic achievement and completion. Therefore, the within-group sample of only AIAN students allows for a more nuanced, context-specific analysis of factors affecting this group of students. The section below provides descriptive statistics of the within-group sample of Native students.

#### Within-Group Sample of American Indian/Alaskan Native Students

Transforming the sample to include only students who identify as American Indian/Alaskan Native for the linear and logistic MLM analyses decreased the overall sample size to 823 students, or 8.55 percent of the full sample (Table 12 below provides descriptive statistics). The within-group sample represents students who graduate at lower rates, dropout at higher rates, and have lower mean achievement on the ACT compared to the full sample. Where only about 5 percent of students drop out in the full sample, almost 10 percent (9.96) dropout in the AIAN sample. The within-group sample is dispersed across 85 schools, where 35 schools have five or more students from the sample and 50 schools have less than 5 students. The students in the within-group overall attend schools with higher poverty and greater Native student populations. The mean IPR value decreased from a mean of 279.20 in the full sample to 212.5 for the AIAN sample. Additionally, over 75 percent of students attend a school that has a school-wide Title 1 program which can often serve as an indicator of schools with greater need. While in the full sample the majority of students attend low Native student density schools (93.25 percent), students' relationship to high and low density schools in the within-group

sample are split more evenly with about 40 percent attending low density and about 60 percent attending high density schools. Similarly, attending a school on- or off-reservation is also more split with about 47 percent attending a school off-reservation and 53 percent attending a school on-reservation. For comparison, almost 94 percent of students attend a school off-reservation in the full sample. The students in the within-group experience substantially more mobility with almost 32 percent of students attending more than one school, while only about 15 percent of students in the full sample attended more than one school. While the proportion of male and female students did not change from the full sample, their relationships to student poverty did. Most students in the within-group are high poverty (82.99 percent) while only about 33 percent are high poverty across all student races. The students in the within-group sample also present different relationships to English Learner status. In the full sample, the majority of students (97.01 percent) were never an English Learner. In contrast, less than 75 percent in the within-group were never an EL, where almost 10 percent identify as a current EL student.

Table 12. Descriptive Statistics of Variables for the Study for Within-Group Sample

<i>Sample Size</i>	<i>n = 823</i>		
<b><i>Continuous Variables</i></b>			
	<i>M</i>	<i>SD</i>	<i>R</i>
<i>Academic Achievement</i>	15.70	3.60	7 to 33
<i>School Poverty</i>	212.5	83.39	98 to 412
<b><i>Categorical Variables</i></b>			
<i>Academic Completion</i>	Dropped Out = 82 (9.96%) Graduated = 741 (90.04%)		
<i>Binary Student Mobility</i>	Mobility = 263 (31.96%) No Mobility = 560 (68.04%)		
<i>Student Mobility</i>	Same System = 560 (68.04%)		

	1 System = 158 (19.20%) 2 Systems = 66 (8.02%) 3 Systems = 28 (3.04%) 4+ Systems = 11 (1.34%)
<i>Gender</i>	Female = 406 (49.33%) Male = 417 (50.67%)
<i>Student Poverty</i>	Low Poverty (Not Eligible for FRPL) = 140 (17.01%) High Poverty (FRPL Eligible) = 683 (82.99%)
<i>English Learner Status</i>	Current English Learner = 80 (9.72%) Former English Learner = 133 (16.16%) Not English Learner = 610 (74.12%)
<i>Native Student Density</i>	0-24% Native student population = 288 (34.99%) 25-49% Native student population = 48 (5.83%) 50-74% Native student population = 72(8.75%) 75-100% Native student population = 415 (50.43%)
<i>Binary Native Student Density</i>	0-49% Native student population = 336 (40.82%) 50-100% Native student population = 487 (59.17%)
<i>School Rurality</i>	Rural (< 25 miles) = 128 (15.55%) Rural (> 25 miles) = 313 (38.03%) Urban = 144 (17.50%) Urban Cluster = 238 (28.92%)
<i>Title 1 Status</i>	Eligible, not participating = 4 (0.49%) Not eligible = 93 (11.30%) School-wide program = 627 (76.18%) Target Assistance = 99 (12.03%)
<i>Reservation Status</i>	Off reservation = 390 (47.39%) On reservation = 433 (52.61%)

There are 139 students missing an ACT score in the AIAN sample, or almost 17 percent (Table 13 below provides descriptive statistics of missing observations). Of the students missing an ACT score, they attended schools essentially the same poverty level as the overall average for within-group ( $M = 195.10$ ), and often attend school on-reservation (61.87 percent). Almost all the students (86.33 percent) attend a school that has a school-wide Title 1 program. These students are predominantly high poverty (92.81 percent) and more likely to be female (57.55 percent). About 35 percent of students missing an ACT score dropped out. Perhaps the most

notable relationship for students missing an ACT score concerns their English Learner status. In the full sample, there are a total of 29 students who are currently EL and missing an ACT score. In the within-group, there are 23 students who are missing an ACT score. This highlights a need for future research to consider AIAN EL students and their participation with standardized assessments in Montana. See Table 13 for descriptive statistics of these 139 students.

**Table 13. Descriptive Statistics of Students Missing ACT Score in Within-Group Sample**

<i>Missing ACT Score</i>	<i>n = 139</i>
<i>School Poverty</i>	<i>M = 195.10, SD = 74.76, R = 98 to 412</i>
<i>Academic Completion</i>	Dropped Out = 48 (34.53%) Graduated = 91 (65.47%)
<i>Binary System Mobility</i>	Mobility = 69 (49.64%) No Mobility = 70 (50.36%)
<i>Gender</i>	Female = 80 (57.55%) Male = 59 (42.45%)
<i>Student Poverty</i>	Low Poverty (Not Eligible for FRPL) = 10 (7.19%) High Poverty (FRPL Eligible) = 129 (92.81 %)
<i>English Learner Status</i>	Current English Learner = 23 (16.55%) Former English Learner = 19 (13.67%) Not English Learner = 97 (69.78%)
<i>Binary Native Student Density</i>	0-49% Native student population = 45 (32.37%) 50-100% Native student population = 94 (67.63%)
<i>School Rurality</i>	Rural (< 25 miles) = 15 (10.79%) Rural (> 25 miles) = 63 (45.32%) Urban = 27 (19.42%) Urban Cluster = 34 (24.46%)
<i>Title I Status</i>	Eligible, not participating = 0 Not eligible = 11 (7.91%) School-wide program = 120 (86.33%) Target Assistance = 8 (5.75%)
<i>Reservation Status</i>	Off reservation = 53 (38.13%) On reservation = 86 (61.87%)

The same data handling choice was applied to the within-group sample as the full sample. Students missing an ACT score represents about 17 percent of the sample, in which case, if mean replacement were to be utilized, it would significantly impact the sample density and normality. In this way, multiple imputation (Rubin, 1987; 1996) is the procedure utilized to handle the 139 observations missing an ACT score. Given the potential impact of missing ACT scores (~17 percent) on the analysis, multiple imputation was conducted with 20 datasets which ensured robustness in the results. Guidelines suggest the number of imputations should be at least as large as the percentage of missing data (Rubin, 1987; 1996). In addition to 20 datasets, data handling also uses PMM with a maximum of 50 iterations and random seed set at 123 for reproducibility. All relevant variables were included in the imputation model, and after the imputation process results were pooled using Rubin's rules to combine estimates and standard errors. Prior to multiple imputation, the mean ACT score was 15.86 for students in the within-group sample. After multiple imputation, the mean ACT score decreased to 15.70. Table 13 above provides the descriptive statistics of ACT after multiple imputation. The sections below provide further detail regarding the dependent and independent variables for the within-group sample.

### Dependent Variables

Academic Achievement. For the within-group sample, scores range from 7 to 33 with an average score ( $M = 15.70$ ) that is 4.01 points lower than the mean for the full sample and 6.30 points lower than the Montana college readiness score. Approximately 17 percent of the within-group sample was missing an ACT score—many of these students also English Language Learners—and these missing observations were handled using multiple imputation. Despite the utilization of multiple imputation to handle the missing ACT observations, normality analysis

including a density plot and QQ plot reveal right-skewed data, or data that concentrates on lower ACT scores with a few high ACT scores pulling the tail to the right. In response, log transformation was applied to the right-skewed multiple imputation completed data. While slightly leptokurtic with more data clustered around the mean, the log transformation to the completed data is approaching a normal distribution and accepted for this study (see Figure 20 and Figure 21 in the Appendix).

ACT achievement by aspects of school location present patterns that are similar to the full sample. For the within-group sample, students off-reservation perform slightly better on the ACT ( $M = 16.46$ ) on average compared to students on-reservation ( $M = 15.00$ ), where students on-reservation score about a point and a half lower on the ACT on average (see Figure 22 in Appendix). Similarly, for the within-group sample, students at low Native student density schools perform about two points better on the ACT ( $M = 16.89$ ) compared to students at high Native student density ( $M = 14.87$ ) schools (see Figure 23 in Appendix). Additionally, there appears to be a linear relationship between ACT achievement and school poverty (see Figure 24 in the Appendix) where students with higher ACT scores are more likely to attend a school with a higher IPR value, or in other words, a lower poverty school. In cadence with existing research and literature, students perform better on the ACT when they attend schools with lower poverty and lower density of minority students.

Academic Completion. Most students graduate in the within-group sample (90.04 percent). Of the 10 percent of students in the sample who dropped out, about 48 percent attended school on-reservation, about 49 percent attended a school with high Native student density, and about 78 percent attended a school with a school-wide Title 1 program. Considering school-level

poverty, there does not appear to be substantial differences in IPR values between students who graduated ( $M = 212.29$ ) and students who dropout out ( $M = 214.44$ ) across Native students (see Figure 25 in Appendix). However, it is interesting to note that students who dropped out attended slightly (approximately two IPR value points) lower poverty schools. This finding in the descriptive statistics opposes existing literature and research, calling for further study. Of students who dropped out, almost 30 percent (28.05 percent) have current or previous identification as an English Language Learner. After exponentiating the log-transformed ACT score means to convert them back to the original ACT score values, students who dropped out (14.75) scored about a point lower than students who graduated ( $M = 15.53$ ) in the within-group sample (see Figure 26 in Appendix). Approximately half of students who drop out experienced mobility and approximately 30 percent of students who graduate experienced mobility, suggesting that students' experiences with mobility may influence dropout likelihood. Using a Pearson's chi-squared test, a significant relationship ( $p < .001$ ) exists between student mobility and academic completion, though Cramer's V (0.1374) indicates this statistically significant relationship is very weak (see Figure 27 in Appendix).

### Independent Variables

Student Poverty. Across the sample, 82.99 percent ( $n = 683$ ) qualified as high poverty while 17.01 percent ( $n = 140$ ) were low poverty. This is a substantial difference from the full sample where the majority of students identified as low poverty. Considering students who graduated in 2019, 82.46 percent were receiving either free or reduced priced lunch (high poverty), while 87.80 percent of students who dropped out were high poverty. Utilizing a Pearson's chi-squared test, a student's poverty as defined by FRPL does not indicate a

statistically significant ( $p = 0.29$ ) relationship to end status. After exponentiating the log-transformed ACT score means to convert them back to the original ACT score values, the mean ACT score for students in high poverty ( $M = 14.96$ ) is almost 3 (three) points lower than the mean ACT score for students in low poverty ( $M = 18.06$ ) (see Figure 28 in Appendix). Almost 35 percent of high poverty students experience mobility (about 10 percentage points higher than in the full sample), while only 18.57 percent of low poverty students experience mobility. Utilizing a Pearson's chi-squared test and Cramer's V, whether students experience mobility shares a statistically significant ( $<.001$ ) but weak (0.13) relationship to student-level poverty.

Additionally, there may be school location relationships to student-level poverty. Most high poverty students attend a school on-reservation (60.62 percent) and with high Native student density (71.16 percent), while most low poverty students attend a school off-reservation (86.43 percent) and with low density (99.29 percent). Naturally, high poverty students attend schools with higher poverty as well, where the average IPR value ( $M = 195.95$ ) is almost 100 points lower compared to the average IPR value ( $M = 293.26$ ) of low poverty students (see Figure 29 in Appendix).

School Poverty. Normality analysis including a density plot and QQ plot reveal right-skewed data, or data that concentrates on lower IPR value scores (higher poverty schools) with a few high IPR value scores (lower poverty schools) pulling the tail to the right. In response, log transformation was applied to the right-skewed data. The log transformed data produces a distribution that is accepted as normal with reasonable dispersion measures (see Figure 30 and Figure 31 in the Appendix). The mean IPR value for schools attended for the within-group sample is lower than the full sample ( $M = 212.5$ ) revealing that students, on average, attend

schools with higher poverty overall in the within-group sample. Examining ACT and school poverty, there appears to be a positive linear relationship where students with higher ACT scores are also more likely to attend a school with a higher IPR value, and vice a versa (see Figure 24 in Appendix). This positive linear relationship mirrors what presents in the full sample between ACT and school poverty. As noted in the section on academic completion, school-level poverty does not appear to have substantial differences in IPR values between students who graduated ( $M = 212.29$ ) and students who dropout out ( $M = 214.44$ ) across Native students (see Figure 25 in Appendix). In addition, this does not appear to have a substantial relationship with students' achievement on the ACT, or in other words, there does not appear to be the kind of relationship where students who attend low poverty schools are more likely to graduate and have a higher score on the ACT (see Figure 32 in Appendix).

Mobility. The descriptive statistics of the full sample revealed that like existing research, there are greater proportions of students experiencing mobility who are of higher poverty and racial minorities. For the within-group Native student sample, about 35 percent of high poverty students experience mobility, which is even 10 percent higher than the full sample. As an unexpected statistic when considering aspects of students' location and mobility, on-reservation students (27.71 percent) have a smaller portion of students attending more than one school (mobility) in their high school experience than off-reservation students (36.67 percent). Utilizing a Pearson's chi-squared test and Cramer's V, whether students experience mobility shares a statistically significant ( $<.01$ ) but weak (0.096) relationship to reservation status (see Figure 33 in Appendix). It is important to note that this is the opposite statistic from the full sample, where

students on-reservation experience more mobility than students off-reservation. The fact this mobility pattern is the opposite when considering Native students requires further investigation.

Considering the outcome variables of academic completion and academic achievement, students' mobility seems to share a relationship with student success to some degree. The mean ACT composite score for students experiencing mobility is 14.83 while students not experiencing mobility is 16.10 (see Figure 34 in Appendix). As stated in the academic completion section above, a significant ( $p < .001$ ) yet weak (0.1374) relationship exists between end status and mobility where students who drop out also experience mobility more than students who graduate. After exponentiating the log-transformed school poverty IPR value score means to convert them back to the original score values, mobility also seems to present a relationship to school poverty as students who experienced mobility attend schools with a mean IPR value of 195.25 while students who did not experience mobility attend schools with a mean IPR value of 198.22 (see Figure 35 in the Appendix).

### Summary of Within-Group Sample

In summary, the within-group sample of Native students presents several notable differences in descriptive statistics compared to the full sample. There is a larger proportion (about a 5 percent increase) of students who drop out and the average achievement on the ACT decreased by 4 points. Further regarding ACT scores, the amount of missing data between the full and within-group sample is also potentially telling. The full sample had about 9 percent missing data while the within-group had almost double at 17 percent. Similar to the full sample, students with experiences of mobility, students living on-reservation, and students attending schools with high poverty all on average have lower ACT scores and more drop out compared to

their Native peers. Quite notable is the proportion of the sample that identifies as high student-level poverty at about 83 percent. Further, student-level poverty seems to present a relationship to ACT achievement as high poverty students score almost 3 points lower than low poverty students.

In the full sample, exploratory analysis reveals statistics in alignment to existing research and literature where higher school and individual poverty seems to be in relation with higher mobility and greater likelihood of dropout. The within-group sample exploratory analysis however reveals some unexpected insight. While the within-group sample overall has greater individual and school-level poverty, mobility and end status trends behave opposite of the full sample. In this way, students who dropped out attended schools with lower levels of poverty (more affluent schools) on average, and students attending school off-reservation had greater proportions of students experiencing mobility. Both trends contrast the full sample and require further investigation.

The proportion of students experiencing mobility overall increased by about 15 percent between the full and within-group sample. It is important to acknowledge again the role of student-level poverty where almost 35 percent of high poverty students in the Native student sample experience mobility, which is about a 10 percent increase compared to the full sample. Lastly, exploratory analysis of the within-group sample reveals noteworthy statistics regarding English Language Learners. While the full sample only had about 3 percent EL students, about one-quarter of the Native student sample is currently or had previously identified as EL. Further, approximately 30 percent of students who dropped out were or are EL, and about 30 percent of students missing an ACT score were EL. The magnitude of statistics on EL students in the Native

student sample is unexpected despite background context of Montana's Consolidated State Plan under the Every Student Succeeds Act (OPI, 2018; 2022) regarding the assessment of EL students (see Literature Review).

### Preparing the Within-Group Sample for Multilevel Modeling

Utilizing a within-group sample for the multilevel model building substantially reduced the total number of schools students attend in the sample. Further, it also reduced the number of students within these schools. The within-group model has 823 Native students across 85 schools. Almost 60 percent of these schools provide an inadequate level-1 sample size where the Native student count is less than 5 students. Ideal minimum sample size requirements for this study would be 50 schools with at least 5 students in each (Bell et al., 2010). However, only 35 schools across the within-group sample have 5 or more students. Due to the small sample size at level-1 across these 85 schools for the within-group sample, this study utilizes robust regression for analysis. Robust linear MLM building uses the "robustlmm" package while the robust logistic MLM building uses the "brms" package in R. MLM remains the best analytical procedure to account for the nesting of students in schools. However, running robust MLM is an approach that attempts to handle violations of typical regression assumptions, such as non-normality or the presence of outliers. Robust MLM adjusts the influence of individual data points by weighting them based on their residuals, helping ensure that highly influential observations do not disproportionately affect the model's estimates. The fixed effects beta coefficients are not altered in robust methods, preserving the relationship between predictors and outcome. Rather, the standard errors are adjusted to better represent the variability in the data, in turn, producing more reliable p-values and confidence intervals (Mehmetoglu & Jakobsen, 2017). The use of

robust linear and logistic MLM strengthens the reliability of the results by addressing potential violations of model assumptions. However, while these methods may help mitigate the influence of outliers or non-normal residuals, they do not completely resolve uncertainty.

### Robust Multilevel Modeling Results

To address the third and fourth research questions, robust linear and logistic multilevel models were used to analyze Native students' academic achievement (ACT scores) and graduation likelihood. For ACT performance, both student- and school-level predictors explained some variation, but most unexplained variance remained at the student level, with student mobility consistently significant across models. In contrast, for graduation likelihood, robust logistic modeling showed that most variance was explained by differences between schools, particularly highlighting the disparity for students attending on-reservation schools. High ICC values (above 85%) underscored the impact of school context on graduation, though most school-level predictors lacked statistical significance, possibly due to overfitting. Comparison of both models suggests the need for further exploration: academic achievement is largely influenced by student-level factors, while academic completion is more affected by school-level factors, revealing distinct influences on these outcomes.

#### RQ 3: Considering Opportunity Factors and Academic Achievement

Table 14 below provides the results for the robust linear MLM models. The robust linear MLM results indicate student level factors might be the key drivers of ACT performance or academic achievement. Though model c is more comprehensive, it introduces non-significant school-level factors, which may suggest potential overfitting. The additional predictors do not

contribute meaningfully to reducing unexplained variance, indicating student-level factors might best help interpret the story of Native student performance on the ACT. Model b—which introduces student variables of gender, English Learner status, and student poverty—provides the best fit as it balances explanatory power and simplicity while also reducing between-school variance. The null model (no predictors) reveals that about 40 percent of the total variance in ACT is attributed to differences between schools, while the remaining variance is due to differences within schools (between students). Model building indicates the majority of variance is explained at the student level. In model a, 38.9 percent of the variance in ACT can be attributed to differences between schools, while the remaining 61.1 percent is due to individual differences between students within schools. Model a is the simplest and shows the strongest effect on mobility, but it does not account for other important factors like gender, poverty, and English Learner status. Model b on the other hand, introduces student characteristics of gender, student poverty and EL status as controls, slightly reducing the effect of mobility while explaining more variance in ACT scores. Model b serves as the best model for balancing simplicity and control. In model b, 35 percent of the variance in ACT can be attributed to differences between schools, while the remaining 65 percent is due to individual differences between students within schools. Model c adds additional school-level factors and offers the most comprehensive understanding of influence on ACT scores, though some of the additional covariates are not significant. In model c, 33.7 percent of the variance in ACT can be attributed to differences between schools, while 66.3 percent is due to individual differences. Table 14 below offers the coefficients, confidence intervals, variance components and fit indices.

Table 14. Robust Linear MLM Results

<i>Variables</i>	<i>Null Model</i>	<i>Model a</i>	<i>Model b</i>	<i>Model c</i>
Intercept	2.765*** (2.73-2.80)	2.730*** (2.70-2.76)	2.578*** (2.55-2.61)	2.119*** (1.23-3.01)
<b>Student Mobility</b>				
<i>No mobility</i>	—	0.041*** (0.04-0.05)	0.033*** (0.03-0.04)	0.033*** (0.03-0.04)
<b>Gender</b>				
<i>Male</i>	—	—	0.007* (0.00-0.01)	0.008** (0.00-0.01)
<b>Student Poverty</b>				
<i>Low poverty</i>	—	—	0.146*** (0.14-0.16)	0.146*** (0.14-0.16)
<b>English Learner</b>				
<i>Former EL</i>	—	—	0.053*** (0.04-0.06)	0.053*** (0.04-0.06)
<i>Never EL</i>	—	—	0.123*** (0.11-0.13)	0.123*** (0.11-0.13)
School Poverty	—	—	—	0.054 (-0.10-0.21)
<b>Reservation Status</b>				
<i>On reservation</i>	—	—	—	-0.036 (-0.16-0.09)
<b>Native Student Density</b>				
<i>Low density (0-49%)</i>	—	—	—	0.010 (-0.13-0.11)
<b>Title 1 Status</b>				
<i>Not eligible</i>	—	—	—	0.190* (-0.01-0.39)
<i>School-wide program</i>	—	—	—	0.226** (0.05-0.40)
<i>Target assistance</i>	—	—	—	0.181* (0.02-0.35)
<b>Rurality</b>				
<i>Rural &gt;25</i>	—	—	—	-0.033 (-0.12-0.06)
<i>Urban</i>	—	—	—	-0.044 (-0.18-0.09)
<i>Urban Cluster</i>	—	—	—	0.011 (-0.09-0.11)
<i>Variance Components</i>				
Student-level variance (within)	0.028	0.028	0.025	0.025
School-level variance (between)	0.019	0.018	0.017	0.017
Adjusted ICC	0.400	0.393	0.400	0.398
Unadjusted ICC	0.400	0.389	0.350	0.337
<i>Fit Indices</i>				
AIC (smaller is better)	-9162.94	-9382.49	-11256.47	-11213.23
BIC (smaller is better)	-9139.69	-9351.49	-11194.48	-11081.46
<i>Nschools</i>	85			
<i>Nstudents</i>	823			

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

Null Model: Intercept-only Model. The intercept-only model includes only the random intercept, which in this study is schools, and no fixed effects (i.e. no predictors). This model serves as a baseline to assess how much variance in academic achievement (ACT scores) can be attributed to schools prior to accounting for any predictors. The null model for the robust linear MLMs revealed significant between-school variation. The random intercept for schools has a variance of 0.019, suggesting that 40 percent of the total variance in ACT could be attributed to differences between schools. The residual variance at the school level is 0.0284, indicating considerable unexplained within-school variation in ACT scores.

Model a: Student Mobility as Predictor. The second model introduces student mobility as a student-level predictor. The fixed effect for no mobility was significant ( $\beta = 0.05, p < .001$ ), indicating students who do not experience mobility have higher ACT scores compared to those who do experience mobility. The inclusion of student mobility in the model did slightly reduce the school-level variance (0.018) compared to the null model which suggests some of the between-school differences in ACT scores can be explained by the variations in student mobility. However, the adjusted ICC remains at 0.393, suggesting that the inclusion of mobility does not dramatically alter the proportion of variance attributed to schools. While student mobility is significant, it does not account for the majority of the between-school differences in ACT scores. The student-level residual variance was largely unchanged (0.0282) compared to the null model. The consistency in student-level residual variance indicates that additional within-school factors are contributing to student ACT score variation.

Model b: Considering Additional Student-Level Factors. Overall, incorporating the student characteristics of gender, student poverty and English Learner status to the model,

slightly reduces the effect of mobility ( $\beta = 0.033, p < .001$ ). Gender is a significant predictor of ACT. The fixed effect for male gender status was significant ( $\beta = 0.007, p < .01$ ), indicating that males have slightly higher ACT scores on average. The fixed-effect for low poverty students was significant ( $\beta = 0.15, p < .001$ ) indicating that students from low poverty backgrounds score higher on the ACT. EL status is also a significant predictor of ACT. The fixed effect for being a previous EL student ( $\beta = 0.05, p < .001$ ) shows significant positive effect, indicating that current EL students have lower ACT scores on average comparatively. Never being an EL student as the largest positive effect on ACT scores ( $\beta = 0.12, p < .001$ ). The inclusion of these two predictors resulted in only a slight reduction in between-school variance to 0.017, a decrease of approximately 0.001. This minimal change is best interpreted as an indication of stability rather than evidence that these student-level factors significantly explain differences between schools. Similarly, the within-school variance showed a minor decrease to 0.025, or about 0.003, which also suggests minimal impact; these student factors do not substantially account for the variation in ACT scores at the student level. The unadjusted ICC decreases slightly to 0.35, suggesting that adding student-level factors provides a marginal explanation for the between-school variance, reflecting individual contributions to school-level differences. However, the adjusted ICC returns to 0.40, reinforcing that even with these predictors, a substantial portion of the variance remains at the school level, indicating limited explanatory power of the added student-level factors.

Model c: Considering Additional School-Level Factors. The final model added reservation status, Native student density, Title 1 status, rurality, and school poverty as predictors, though most of these school-level predictors were not significant. Overall, the incorporation of these factors does not further reduce the effect of mobility ( $\beta = 0.033, p < .001$ ),

but also does little to explain more of the variance in ACT scores as well. Similar to model b, the final model suggests males on average score higher on the ACT ( $\beta = 0.008, p < .001$ ). Low student poverty ( $\beta = 0.15, p < .001$ ) and EL status remain significant and unchanged, where not being a current EL student also has its slight advantage on ACT achievement (Previous EL student:  $\beta = 0.05, p < .001$ ; Never an EL student:  $\beta = 0.12, p < .001$ ). The fixed effect of Title 1 status is significant, most notably, that schools participating in a Title 1 program have higher ACT scores on average (Targeted Assistance:  $\beta = 0.18, p < .01$ ; School-wide Program:  $\beta = 0.25, p < .01$ ). The rest of the school-level factors of the final model are not statistically significant. School-level poverty ( $\beta = 0.05$ ), as captured by IPR values, suggested a positive (more affluent schools are associated with higher ACT scores) but non-significant on effect ACT. Attending a school on-reservation ( $\beta = -0.04$ ) is associated with slightly lower ACT scores on average compared to attending a school off-reservation, though this result is not statistically significant. Attending a school with low Native student density ( $\beta = 0.01$ ), or a school with less than 49 percent of its student identifying as American Indian/Alaska Native, is perhaps associated with slightly higher ACT scores, though the result is not statistically significant. Students attending schools that are rural and more than 25 miles from an urban cluster ( $-0.03$ ), as well as student attending schools in urban places ( $-0.05$ ) are associated with perhaps lower ACT score averages, but these results lack statistical significance. Despite adding school-level variables, the between-school variance persists from model b at 0.017, indicating the school-level factors do not help explain more of the between-school differences in ACT achievement. The unadjusted ICC reduces to 0.34, suggesting these school-level factors begin to explain more of the between-school differences. However, the adjusted ICC is slightly lower at 0.398, indicating that while

school-level predictors contribute to the overall model, a considerable portion of the variance remains unexplained. The minimal change in adjusted ICC indicates that these school-level variables do not drastically improve the model's ability to explain school-level variance. Lastly, the residual deviance remains unchanged at 0.025, suggesting that these school-level variables do not explain much additional variance in ACT performance. Other unmeasured factors, likely at the student level, may be influencing ACT scores that should be explored with further investigation.

Diagnostic Test Results. Diagnostic tests for the level-1 residuals (see Figures 36-37 in Appendix) are accepted as normal for this study. Diagnostic tests of multicollinearity reveal that none of the predictors in the final model exhibit high multicollinearity ( $< 5$ ) where the largest values are for reservation status (1.67) and Native student density (1.82). Visualizing the between-school variability in ACT scores (see Figure 38) to understand how individual schools deviate from the overall trend captured in the model, reveals that most schools do not significantly deviate from the overall fixed intercept in the model. It appears the random intercepts for the schools capture the between-school variation, with some schools performing slightly better or worse on average. There are a few schools which might be slightly farther from zero than the majority of schools, though these are not extreme enough to be investigated as outliers. Examining the fit of the linear MLM regression model (see Figure 39), it appears the majority of the predicted outcomes cluster around lower values. This may imply the model predicts lower values more frequently, potentially due to the distribution of ACT scores for Native students. While the residuals cluster is concentrated toward lower ranges, it forms a random cloud of points with no visible patterns suggesting the model fits well. There are what

appears to be observations (see red points in Figure 39) outside of the main residual cluster which fall close to the reference line, indicating these data points were predicted near exact by the model. Upon examining further, these points represent 147 high-fitted points of students attending on-reservation and high poverty schools (almost 80 percent), and with a wide range of ACT scores (range 9 to 24, though the majority of scores cluster around 13 to 16). These students appear to show higher predicted ACT values than the rest of the data. Mahalanobis distance is utilized to further analyze these 147 observations by measuring how far each point is from the mean in the distribution, considering the covariance of variables involved. A larger Mahalanobis distance indicates that a point is farther from the center of the data distribution and may be an outlier. Using Mahalanobis distance, the top 1 percent of the most extreme observations were gathered and further examined to reveal even distribution (see Figure 40 in Appendix). It is concluded these observations are likely the result of natural data variability rather than systematic bias or error. Overall, diagnostic testing for the robust linear MLM determines normality of the residuals (see Figure 41 in Appendix).

Summary. Overall, these models reveal that while both student- and school-level predictors contribute to explaining the variation in ACT scores, the majority of unexplained variance remains at the student level. The inclusion of student mobility, student gender, student poverty, and student EL status and the school-level predictor of Title 1 status effectively reduced the between-school variance. However, the majority of the variation in ACT scores remains unexplained within schools as revealed in the proportion of variance attributed to the student level compared to the school level. The persistent residual variance (0.028 to 0.025, or a 0.003 decrease across models) indicates that factors not captured by the models such as additional

student-level factors or interactions still account for a substantial portion of the variation in ACT scores. In this way, most of the variance in ACT is explained by within-school differences (student-level variation) rather than by differences between schools. The final model suggests that addressing the variety of school-level factors alone may not offer a sufficient approach to explaining student performance disparities fully for the within-group sample of Native students in Montana. These findings highlight the complexity of academic performance, suggesting that individual characteristics and experiences play a more significant role than school-level factors alone in shaping ACT outcomes for Native students in Montana.

#### RQ 4: Considering Opportunity Factors and Academic Completion

Table 15 below provides the results for the robust logistic MLM models. The robust logistic MLM results indicate model b appears to be the best fit, providing a balance between simplicity and explanatory power. It captures important student-level effects without introducing the high level of uncertainty seen in model c. While providing more detailed school-level information, model c introduces high uncertainty for many covariates and may suffer from overfitting which can be observed in the large confidence intervals and imprecise intercept estimate. The null model (no predictors) reveals that about 87 percent of the total variance in students' graduation likelihood is attributed to differences between schools, while the remaining variance is due to differences within schools (between students). This high ICC suggests that a substantial portion of the variance in academic completion (graduation likelihood) is due to differences between schools. Across all models, the ICC values remain high (> 85 percent), indicating that the majority of variance in academic completion is explained by differences between schools. In fact, the increase of ICC from the null model to the final model

(approximately 86 to 90 percent) suggests that adding school-level predictors enhances the model's ability to explain variance between schools, perhaps emphasizing the importance of school context on graduation likelihood. However, many of the added school-level variables are not statistically significant. Model a is the simplest with a significant effect on student mobility, but it does not account for other important factors like gender, student poverty and English Learner status. Model b on the other hand, maintains a significant and nearly unchanged effect of mobility from model a, but introduces student-level variables as controls. Model b serves as the best model for balancing simplicity and control. In model b, 86.4 percent of the variance can be attributed to differences between schools, while the remaining 13.6 percent is due to individual differences between students within schools. The added complexity of model c produces results that are more uncertain suggesting possible overfitting. Table 15 below offers the coefficients, confidence intervals, variance components and fit indices. It is important to note the fixed nature of individual-level (student-level) variance in logistic MLM (Gelman, 2007), in which case only school-level variance is reported. Additionally, Leave-one-out Cross-Validation (LOO-CV) is a model validation technique utilized in addition to AIC. In Bayesian models, LOO-CV provides more robust estimates and is particularly beneficial for complex models where overfitting is a concern (Gelman et al., 2013) such as seen in this study.

Table 15. Robust Logistic MLM Results

<i>Variables</i>	<i>Null Model</i>	<i>Model a</i>	<i>Model b</i>	<i>Model c</i>
Intercept	6.25*** (4.79-8.19)	4.96*** (3.68-6.60)	4.32*** (2.96-6.07)	24.08 (-14.63-64.25)
<b>Student Mobility</b>				
<i>no mobility</i>	—	1.39*** (1.26-1.53)	1.35*** (1.22-1.48)	1.35*** (1.22-1.48)
<b>Gender</b>				
<i>Male</i>	—	—	-0.69*** (-0.80 to -0.57)	-0.69*** (-0.81-0.57)
<b>English Learner</b>				
<i>Former EL</i>	—	—	1.14*** (0.91-1.36)	1.14*** (0.93-1.36)
<i>Never EL</i>	—	—	0.84*** (0.67-1.01)	0.84*** (0.67-1.01)
<b>Student Poverty</b>				
<i>Low Poverty</i>	—	—	0.87*** (0.65-1.10)	0.87*** (0.66-1.08)
School Poverty	—	—	—	-1.91 (-8.80-4.87)
<b>Reservation Status</b>				
<i>On reservation</i>	—	—	—	-7.72** (-14.27 to -2.07)
<b>Native Student Density</b>				
<i>Low density (0-49%)</i>	—	—	—	-2.43 (-8.14-3.44)
<b>Title 1 Status</b>				
<i>Not eligible</i>	—	—	—	-2.43 (-13.13-6.44)
<i>School-wide program</i>	—	—	—	-4.70 (-14.78-3.78)
<i>Target assistance</i>	—	—	—	-4.88 (-14.81-3.41)
<b>Rurality</b>				
<i>Rural &gt;25</i>	—	—	—	0.83 (-3.81-5.29)
<i>Urban</i>	—	—	—	-4.21 (-10.28-1.32)
<i>Urban Cluster</i>	—	—	—	-1.31 (-6.31-3.36)
<i>Variance Components</i>				
School-level variance (between)	4.73	4.48	4.57	5.28
Adjusted ICC	0.872	0.859	0.864	0.895
Unadjusted ICC	0.872	0.844	0.837	0.711
<i>Fit Indices</i>				
AIC	9292.60	8825.41	8471.92	8477.18
LOO_CV	9103.10	8638.30	8284.10	8279.10
<i>Nschools</i>	85			
<i>Nstudents</i>	823			

\*\*\*  $p < 0.001$ ; \*\*  $p < 0.01$ ; \*  $p < 0.05$

Null Model: Intercept-only Model. The intercept-only model includes only the random intercept, which in this study is schools, and no fixed effects (i.e. no predictors). This model serves as a baseline to assess how much variance in academic completion can be attributed to schools prior to accounting for any predictors. The null model for the robust logistic MLMs

revealed significant between-school variation. The random intercept for schools has a variance of 6.25 and the odds ratio for the intercept is very high at 515.94, indicating that the overall likelihood of graduating is extremely high (approximately 99.8 percent) when no other factors are included. The null model ICC suggests that about 87 percent of the total variance in academic completion could be attributed to differences between schools. This highlights the significant role that school-level factors play in explaining variance in student outcomes even in the absence of predictors. The high ICC attributing the differences between schools also leaves only a small portion (approximately 13 percent) attributable to the differences between students. Similarly, the residual variance at the school level is 4.73, indicating substantial differences between schools in predicting academic completion.

Model a: Student Mobility as Predictor. The second model introduces student mobility as a student-level predictor with an intercept that is statistically significant ( $\beta = 4.96, p < .001$ ). The fixed-effect for no mobility had significantly high odds of graduation ( $\beta = 1.39, p < .001$ ) where students are 4.03 times more likely to graduate than students who experience mobility in the Native within-group sample of students. The ICC slightly decreased to 0.859, indicating that student mobility explains some of the variance between schools. School-level variance in the second model reduced to 4.48, though it still remains relatively large. This indicates notable variability in student graduation outcomes across schools where some schools may have higher overall odds of graduating than others. While student mobility accounted for some of the between-school differences, a large portion of variance still exists at the school level.

Model b: Considering Additional Student-Level Factors. Incorporating student characteristics of gender, student poverty and English Learner status to the model, kept the effect

of mobility relatively stable and as a strong predictor of graduation likelihood ( $\beta = 1.35, p < .001$ ), where students who remain in the same school throughout their high school experience are 3.86 times more likely to graduate compared to their Native peers who experience mobility. Gender is a significant predictor of graduation. The fixed effect for male gender status was significant ( $\beta = -0.69, p < .001$ ), and an odds ratio of 0.50 indicates that males are about 50 percent less likely to graduate compared to female students. This means that male students have approximately a 33 percent likelihood of graduating compared to females, indicating a reduced likelihood for males. The fixed-effect for low poverty students was a significant ( $\beta = 0.87, p < .001$ ) predictor of graduation with an odds ratio of 2.32 indicating low poverty students are 2.32 times more likely to graduate compared to their high poverty peers. EL status is also a significant predictor of graduation. The fixed effect for being a previous EL student ( $\beta = 1.14, p < .001$ ) shows significant positive effect, indicating higher odds (3.13) of graduating compared to students who are current ELs. Never being an EL student does not align with the largest positive effect on graduation the way that never being an EL aligned to the largest positive effect on ACT achievement. While students who were never an EL student do have significantly ( $\beta = 0.84, p < .001$ ) higher odds of success than current EL students (2.32), students with former EL status have the highest odds of successfully graduating among Native students.

The inclusion of gender, student poverty, and EL status reduced the between-school variance slightly to 4.57, indicating that accounting for these student-level factors explained more of the differences between schools. Similar to previous models, this school-level variance remains relatively large, revealing continued variability in graduation outcomes across schools. Further, the inclusion of these student-level predictors slightly increased the adjusted ICC to

0.864, while the unadjusted ICC decreased to 0.837, suggesting that individual characteristics explained some of the variance in graduation outcomes, though school-level differences remain substantial. Model b shows further improvement in fit, with AIC (8471.92) and LOO-CV (8284.10) scores continuing to decline, marking this model as the most balanced in terms of simplicity and explanatory power.

Model c: Considering Additional School-Level Factors. The final model added reservation status, Native student density, Title 1 status, rurality, and school poverty as predictors, though these additions produced results that are more uncertain as reflected by wide confidence intervals. Overall, the incorporation of these factors produced a large, imprecise estimate with no statistical significance ( $\beta = 24.08$ , CI = -14.63 to 64.25) suggesting high uncertainty. Caution should be taken when interpreting the effects of these additional variables, with reservation status perhaps as an exception. While the model attempts to capture nuances at the school level, the high level of uncertainty points to the need for further refinement or validation with larger datasets. While student-level predictors of mobility ( $\beta = 1.35$ ,  $p < .001$ , OR = 3.86), gender ( $\beta = -0.69$ ,  $p < .001$ , OR = 0.50), student poverty ( $\beta = 0.87$ ,  $p < .001$ , OR = 2.38) and EL status (Previous EL student:  $\beta = 1.14$ ,  $p < .001$ , OR = 3.13; Never an EL student:  $\beta = 0.84$ ,  $p < .001$ , OR = 2.31) remained consistent and significant similar to previous models, only reservation status as a school-level predictor showed a significant effect on graduation. Schools located on-reservation were associated with significantly lower odds of student completion (Estimate = -7.72,  $p < .01$ ). The odds ratio of 0.0004 indicates that students attending on-reservation schools are overwhelmingly less likely to graduate compared to their peers in off-reservation schools. Specifically, the odds of graduating for students attending schools on-

reservation are reduced by approximately 99.95 percent. This result highlights a dramatic disparity in graduation outcomes between students attending schools on-reservation and those attending schools off-reservation, suggesting that attending an on-reservation school is a substantial barrier to academic completion, even when other factors like mobility, gender, and English Learner status are taken into account. All other school-level predictors added to this model are not statistically significant and showed wide confidence intervals, reflecting uncertainty in their effects.

The school-level variance increased to 5.28 in this final model, indicating that the inclusion of these school-level factors captured important differences between schools, but a significant proportion of the variance still remains unexplained within schools. The adjusted ICC increased notably to 0.895, suggesting that the addition of school-level factors helps explain more of the between-school variance. However, the unadjusted ICC dropped to 0.711, reflecting the complexity introduced by adding these school-level predictors that did not explain the variance as effectively. Despite the additional school-level predictors, the fit indices (AIC = 8477.18 and LOO-CV = 8279.10) are only marginally better than the fit indices for model b. This suggests the additional school-level variables provide little practical improvement in model fit. Further, the high uncertainty and wide confidence intervals for several of these predictors suggest potential overfitting.

Diagnostic Tests Results. The final model of the robust logistic MLM analysis produced a receiver operating characteristic (ROC) curve (see Figure 42) that demonstrates the model has adequate performance between sensitivity (true positive rate) and specificity (false positive rate). The area under the curve (AUC) value is 0.8425 indicating a strong level of discriminatory

ability for the model, or that there is an 84.25 percent chance the model will correctly rank a randomly chosen graduate higher than a randomly chosen dropout based on predicted probabilities. This AUC value falls on the scale of interpretation of excellent discrimination suggesting this model is effective at distinguishing between students who are likely to graduate versus those who dropout, based on the predictors used in the model. For comparison, the ROC curve and AUC value (0.8424) for model b show essentially the same results as model c. The confusion matrix for the final model is provided via Table 16 below where true positives are students who graduated and were correctly predicted by the model as graduating.

Table 16. Confusion Matrix of Final Robust Logistic MLM

	<i>Actual Dropout</i>	<i>Actual Graduate</i>
<i>Predicted Dropout</i>	1.70 percent (True Negative)	0.61 percent (False Negative)
<i>Predicted Graduate</i>	8.26 percent (False Positive)	89.43 percent (True Positive)

The results of the confusion matrix articulate how often the model correctly classified students as either graduating or dropping out with approximately 90 percent accuracy. True events are where the model accurately predicted the actual end status of the student where true positive is the prediction of graduate and the student graduates, while true negative is the prediction of dropout and the student drops out. Inversely, false events are where the model was inadequate: false positives represents when the model predicts the student with graduate, but actually dropped out (type I error) while false negative represents when the model predicts the student will dropout, but actually graduated (type II error). Considering sensitivity by students who actually graduate (true positive + false negative), the proportion of actual graduates correctly identified by the model is high at 99.3 percent. Considering sensitivity by students who

actually dropout (true negative + false positive), the proportion of non-graduates correctly identified by the model is low at about 17 percent. Considering precision by predicted graduates (true positives + false positives), the model is accurate in identifying students who graduate 91.5 percent of the time. In summary, the final model of the robust logistic MLM analysis performs well in identifying students who graduate. However, the model has a high count of false positives and low specificity, meaning it is not as effective at identifying students who dropout.

Diagnostic tests of multicollinearity reveal that none of the predictors in the final model exhibit high multicollinearity ( $< 5$ ) where the largest values are for school-poverty (2.30) and Native student density (2.26). Diagnostic tests on the model's residuals reveals the possibility of overfitting due to the complexity introduced by the final model. The plot of binned residuals (see Figure 43 in Appendix) presents inconsistent error bars, indicating less reliable estimates and that there may be bins lacking observations to produce reliable estimates. Further, the plot suggests underfitting for lower fitted values and possible overfitting or captured noise at higher fitting values. As anticipated analyzing the robust logistic MLM results—particularly unexplained variance—the model likely requires further refinement exploring more predictors and interactions, especially at the school-level.

Summary. Overall, the robust logistic MLM results reveal that student-level factors, particularly mobility, gender, student poverty, and English Learner status, are significant predictors of graduation. While school-level variance explains a large portion of the variability in graduation rates, especially in the null model, the inclusion of student-level predictors substantially improved the explanatory power in model a and model b. Odds ratios highlight the significant role of student mobility and EL status in graduation, especially when students have no

experiences with mobility and are a former EL student. Despite the role of these student-level predictors, the random effects suggest that schools still have a considerable influence on the outcome of graduation, when accounting for individual differences. Further investigation is needed to capture the remaining unexplained variance, particularly at the school level.

### Chapter Summary

In this chapter, varying approaches to regression analysis are used to answer the four research questions under investigation. To answer the first research question, linear regression was utilized to examine the relationship between student characteristics of gender, race and poverty on their academic achievement which is measured by ACT score. Effect coding compares each of these levels to the grand mean prior to analyzing by all possible interactions between these intersecting social locations in a statistically significant saturated linear model. Overall, the saturated model indicates that gender, race and student poverty have significant impacts on academic achievement, however the lack of significant three-way interaction effects perhaps suggests that these factors operate relatively independently of one another. The social location of AIAN-high poverty students as well as male-high poverty students are the unique exceptions. One interesting development to note in the linear regression models is the change in effect for male students: In effect coding, male students perform better on the ACT compared to females, however in the saturated model, male students perform worse on the ACT compared to females when controlling for race, student poverty, and the interactions of the student characteristics.

To answer the second research question, logistic regression was utilized to examine the relationship between student characteristics of gender, race, and poverty on their academic

completion which is a binary outcome for an end status of graduate and dropout. Effect coding and a saturated model were explored, similar to the linear regression models. Effect coding found males, AIAN, and high poverty students may be of careful consideration as they present results that are less likely to graduate compared to their white, female, low poverty peers. While none of the three-way interactions were significant in the saturated model, the interaction between being male and high poverty has a significant negative effect on graduation likelihood. There is also a significant negative effect between being male and Hispanic, however this study makes a difficult decision in alignment to policy, literature, and in light of the majority of the results for research questions one and two—most results point to unique significant relationships for AIAN, male and high poverty students—of how to focus analysis to answer the third and fourth research questions by using a within-group sample of Native students.

The within-group sample ( $n = 823$ ) of Native students represents students who graduate at lower rates, dropout at higher rates, and have lower mean achievement on the ACT compared to the full sample. Student-level and school-level poverty also notably increased for the within-group sample. The school location indicators of reservation status and Native student density are more split in the within-group sample where most students in the full sample attend low Native student density schools and off-reservation schools. Perhaps most unexpected is the presence of English Learners in the within-group sample where about a quarter of the students have formerly or are currently identified as EL. Further, of students missing an ACT score in the within-group sample, 23 are a current EL which is about 80 percent of current EL students in the full sample missing an ACT score. This highlights a need for future research to consider Native EL students and their participation with standardized assessments in Montana. Mobility and end status trends

behave opposite of the full sample. In this way, Native students who dropped out attended schools with lower levels of poverty (more affluent schools) on average, and Native students attending school off-reservation had greater proportions of students experiencing mobility. Both trends contrast the full sample and require further investigation.

To answer the third research question, robust linear multilevel modeling incorporates multiple predictors representative of opportunity factors Native students in the within-group sample may face in relation to their academic achievement (ACT score). Overall, both student- and school-level predictors contribute to explaining the variation in ACT scores, but the majority of unexplained variance remains at the student level. Student mobility remains significant across models, but the residual deviance is also persistent indicating most of the variance in ACT is explained by within-school differences rather than differences between schools. Despite this, the final model which contains the full set of student and school controls provides the most nuanced understanding. In the final model, students who remain at the same school throughout their high school experience (no mobility), are male and have never been an English Learner perform better on the ACT compared to peers who experience mobility, are female, and are currently or formerly been identified as an EL. While schools participating in a Title 1 program have higher ACT scores on average, the remaining school-level factors are not statistically significant indicating that addressing these alone may not offer a sufficient approach to explaining student performance for Native students in Montana.

To answer the fourth and final research question, robust logistic multilevel modeling mimics the model building of the robust linear MLM but with the binary outcome predicting graduation likelihood. While including the full set of student and school controls in the robust

linear MLM provided the most comprehensive and nuanced approach, this final model for the robust logistic MLM introduces high uncertainty for many covariates and likely suffers from overfitting. Across all models, the ICC values remain high ( $> 85$  percent), indicating that the majority of variance in academic completion is explained by differences between schools. In fact, the increase of ICC from the null model to the final model (87 to 89 percent) suggests that adding school-level predictors enhances the model's ability to explain variance between schools, perhaps emphasizing the importance of school context on graduation likelihood. However, many of the added school-level variables are not statistically significant and the incorporation of these factors produced a large and imprecise estimate with no statistical significance. While interpreting the effects of the additional variables should be considered with caution, student mobility remained significant across models, and the final model reveals in particular the dramatic disparity in graduation outcomes between students attending schools on-reservation. ROC curve and AUC value as diagnostic tests of the final model indicate a strong level of discriminatory ability in the model. Further, use of a confusion matrix reveals the final model is excellent at identifying students who graduate, however the model is not as effective at identifying students who dropout.

Comparing the findings of the robust linear MLM and the robust logistic MLM, the unexplained variance in each analysis seem to offer a need to explore opposing stories in terms of student success. The results of the robust logistic MLM primarily point to the need for further investigation to capture the remaining unexplained variance, particularly at the school level. This need for further investigation at the school level is particularly interesting when compared to the results of the robust linear MLM which indicated the majority of unexplained variance remains

at the student level. In this way, the two outcome variables for academic success reveal somewhat opposing insight, where academic achievement (ACT performance) has the majority of unexplained variance at the student level and academic completion (graduation likelihood) has the majority of unexplained variance at the school level.

## CHAPTER FIVE

## CONCLUSIONS

This study's findings highlight that academic success in Montana is not solely a matter of individual capabilities but is profoundly influenced by intersecting structural factors like poverty, mobility, race, and cultural belonging. To move beyond simple "achievement gap" metrics, Montana must adopt an intersectional approach that acknowledges the unique barriers and strengths of diverse student groups. This requires ongoing support for culturally responsive policies, improved teacher recruitment in rural areas, and expanded reporting metrics that reflect the complex realities of student achievement in Montana.

Research Questions

This study was guided by four primary research questions:

1. Are there observable differences by academic achievement based on students' social location orientation (gender, race, class)?
2. Are there observable differences by academic completion based on students' social location orientation (gender, race, class)?
3. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic achievement?
4. How do individual student opportunity factors (i.e. student poverty and student mobility) and school-level opportunity factors (i.e. school poverty) influence students' academic completion?

### Summary of Methodology

This study is a nonexperimental research design involving analysis of longitudinal student-level and school-level data following a single cohort of Montana high school students. Quantitative analysis explores the research questions where student success outcomes are captured in two primary ways: 1) academic achievement, measured as ACT composite scores, and 2) academic completion, measured as a binary graduate/dropout end status variable. These two outcome measures are in alignment with existing literature, policy and reporting of the Montana “achievement gap.” The independent factors of poverty and mobility stressed in this study focus on illuminating where current “achievement gap” reporting is inadequate. These independent factors, or opportunity factors, reveal aspects of students’ academic experience which may better inform disparity between achievement and completion for Montana students. The full sample ( $n = 9,621$ ) of Montana students includes all racial categories, where the majority identify as white and the second largest category by race is students who identify as American Indian/Alaskan Native (AIAN). The full sample was used to address the first two research questions through regression model building.

Linear regression was utilized to answer research question 1 where the outcome variable is academic achievement (ACT scores). Logistic regression was used to answer research question 2 where the outcome variable is academic completion (graduate/dropout). However, the approach of model building is mirrored between research questions 1 and 2. In this way, effect coding first establishes the unique relationships gender, race and student poverty have with the outcome variables. Next, a saturated model explores social locations through a full set of gender, race and student poverty variables, as well as all possible interactions between, and the

relationship to the two academic success (achievement and completion) outcome variables. For the two saturated models, marginal effects are reported where the reference group is white, low-poverty, females.

The results addressing the first two research questions revealed distinct needs and contexts for AIAN students compared to other racial groups in Montana, particularly white students. To answer research questions 3 and 4, analysis utilizes a within-group sample ( $n = 823$ ) of only AIAN students in hope to avoid aggregation bias where the unique challenges of these students become invisible in the broader sample. Additionally, existing data and policy—namely that surrounding “achievement gap” policy—declare a need to better understand the unique experience of Native students toward academic success. The within-group sample allows for a more nuanced, context-specific analysis of factors affecting this group of students. To answer research questions 3 and 4, robust multilevel modeling (MLM) is utilized. Robust linear MLM considers student and school-level factors when the outcome variable is ACT performance or academic achievement, while robust logistic MLM is used when the outcome is the binary end status variable for academic completion. Similar to the first stage of model building, the MLM work is mirrored between research questions 3 and 4. After establishing a null model, the independent variable of student mobility was added first and in isolation, prior to adding in the sets of school and student controls. Next, a set of student-level controls (gender, student poverty, and English Learner status) were added to the model. Last, a set of school-level controls (school poverty, reservation status, Native student density, Title 1 status, and rurality) were added to the model. The study’s results are summarized alongside relevant literature to underscore key findings and their implications.

### Interpretation & Implication of Findings

#### RQ 1 & RQ 2: Social Locations and Academic Success

Across gender, race and student-level poverty, effect coding analysis showed the amount of variance explained by these models is relatively modest despite their statistical significance, suggesting there are other factors which may also contribute to differences in academic success aside from gender, race and student poverty. This aligns to the understanding that there are a range of opportunity factors impacting students' academic success (Boykin & Noguera, 2011; Mark, 2013; Milner, 2010). These results emphasize the need for analysis to consider such opportunity factors at the student level such as mobility (Hanushek et al., 2004; Schwartz et al., 2009; South et al., 2007; Xu et al., 2009), as well as the school level factors such as school poverty (Anderson et al., 1992; Andrews et al., 2003; Berliner, 2009; Gottlieb, 2002; Kahlenberg, 2004; Rumberger & Palardy, 2002; Rusk, 2002; Tschinkel, 1999). The saturated models and marginal effects (López et al., 2018) reveal there are students in Montana whose intersectional identities experience compounded barriers to academic success, despite small group sizes and diminished statistical power in creating the 28 social locations. These groups of students confirm Montana needs to broaden awareness, reporting and policy from the binary racial reporting between Native and non-Native students currently exercised to reports which allow investigation across all Montana students.

Effect Coding. Effect coding reveals male students score slightly higher on the ACT and are more likely to graduate compared to females with both statistical and practical significance. The importance of effect coding is palpable within these results, as it is used to understand the unique variables' relationship to the group means prior to analyzing by intersecting social

locations in the saturated models, or further as a control in the MLM models. In nearly all other models in this study, females scored higher on the ACT and were more likely to graduate compared to males. The fact that males attain higher academic success (as defined by the two outcome variables of this study) than females when conducting effect coding seems to suggest that when analyzing without controlling for additional student- and school-level factors, males perhaps benefit from certain systemic or contextual advantages. However, when student poverty and race are added to the model, females outperform males. Similarly in the later MLM analysis of the within-group sample, adding student factors of mobility and English learner status, as well as other school-level controls, Native females outperform Native males. In other words, the positive results for males in the effect coding are reversed once other factors are taken into consideration. This may point to an unexpected finding of resilience in female students where they are more likely to overcome barriers such as mobility or poverty.

In a study by DiPrete and Buchmann (2013) results found female students outperformed males in educational attainment despite similar levels of socioeconomic disadvantage. The researchers attributed the difference to greater self-regulation, academic motivation and social support experienced by female students. Mickelson and Greene (2006) found female students, particularly those from low socioeconomic backgrounds, can develop a greater sense of resilience and motivation. In another study (Hubbard, 2006) that found female students more successful than their male peers, particular attention on students who faced discrimination revealed these female students were less likely to ignore discrimination and actually more willing to challenge the institution. The researcher noted their resilience in academic persistence.

Saturated Models. In both the linear and logistic saturated models, being male and coming from a high poverty background are independently associated with lower ACT scores and lower likelihood of graduation. Further, the interaction between gender and poverty reveals even more pronounced effect suggesting that male students from high poverty backgrounds face compounded disadvantage. In the linear saturated model, identifying as AIAN is independently associated with lower ACT scores, however the interaction between race and poverty reveals even more pronounced effect for AIAN students in high poverty. These significant two-way interactions indicate that the combined impact of these identities on academic outcomes exceeds the individual effect of each identity on its own.

Considering compounded disadvantage is imperative to better understand how social inequity accumulates across social locations. For example, male students in high poverty backgrounds may face additional barriers or even bias (i.e. lower expectations) limiting their opportunity of academic achievement in different or pronounced ways compared to their peers. Some research indicates educators perceive male students, particularly those from disadvantaged backgrounds, as less academically capable (Auwarter & Aruguete, 2010) and harder to teach, even as early as within the first two years of school (Childs & McKay, 2001). The stereotyping of educators and biases in the educational system (Entwisle et al., 2007) could lead to issues with equitable treatment in the classroom which could certainly impact testing achievement. Other research reveals that male students, particularly from lower-income families, face systemic barriers in school environments (Gershenson et al., 2016), and even cultural biases that prioritize female students' success (Auwarter & Aruguete, 2010).

Similarly, AIAN students from high poverty may experience structural disadvantage such as limited access to high-quality schools, culturally responsive teaching, or support programs. Substantial literature addresses the unique barriers and structural disadvantages faced by Native students. Castagno and Brayboy (2008) argue that Native students face systemic disadvantages stemming from underfunding schools, not uncommonly, schools on-reservation. Native students are also disproportionately likely to live in poverty (Pew Research Center, 2014) presenting additional barriers such as food insecurity or unstable housing, which of course could compound challenges students face in school exacerbating educational inequity for these students. In broad sweeps, the structural disadvantage Native students face as a long-standing effect of colonization and displacement (Brayboy, 2005), present structural barriers in abundance: implicit bias from educators (Tenenbaum & Ruck, 2007), deficit thinking in the school systems (McCarty & Lee, 2014), lack of cultural responsiveness in schools (Faircloth & Tippeconnic, 2010), pressure to assimilate and cultural incongruence (Lomawaima & McCarty, 2006), and language barriers (Reyhner & Eder, 2004).

The interaction effects between variables demonstrate that disparities are not simply additive, but exponential. In other words, the challenges AIAN students in high poverty face in performance on the ACT are not just the sum of challenges between being AIAN and coming from a high poverty context, but rather challenges are compounded by the interaction of these identities. This compounding disadvantage supports the idea that students who occupy multiple marginalized identities face greater barriers to academic success than would be expected from looking at these factors independently. This aligns to the findings and recommendations articulated by López and team's quantitative intersectionality project (2018). Such quantitative

strategy attempts to highlight the complicated nature of race-gender-class gaps in education (Bowleg 2008; Davis, 2008; Davis et al., 2015; López et al., 2018; Mitchell 2014) following the call to deracialize statistics (Zuberi, 2001) rather than follow the cadence of most research which *control* for race. López and team's findings in 2018 found nearly<sup>5</sup> every gender-race-class group had significantly lower likelihood of graduation compared to low-poverty, white, females. In particular, male American Indian students from high poverty were approximately 45 percent less likely to graduate and female American Indian students from high poverty were approximately 40 percent less likely to graduate. These intersecting identities experience “disadvantage accruing” and “offer promising strategies for conceptualizing race as a relational social status embedded in a given sociohistorical context” (pg. 200). In this way, the compounded barriers to academic success that AIAN high-poverty and male high-poverty students face in Montana are flags to unearth the sociohistorical contexts and structural inequities these students navigate in order to articulate opportunity gaps. If we stop at reporting that these two groups of students simply underperform compared to their peers, all we have done is coin “achievement gaps” as an intersectional project.

Interestingly, none of the three-way interaction effects—effects that would capture the combined influence of race, gender and poverty—have statistically significant impacts on ACT scores or likelihood to graduate. While each of these factors are impactful on their own, they may not interact in a way that produces exponential barriers beyond the two-way interactions. For example, being AIAN, male, and from high poverty are each significant in isolation on ACT performance, and the two way combinations are significant, but the three-way interaction does

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<sup>5</sup> Except for high-income Hispanic women and Asian women.

not reveal additional compounded disadvantage. The small sample size of most racial groups in Montana could be at play, especially considering that the three-way social locations further disaggregate these small racial groups limiting the statistical power to detect significant effects. Future replication of such an intersectional project of Montana students might consider aggregating students into fewer racial categories.

RQ1 & RQ2 Summary. Across all models addressing the first two research questions, student poverty has significant statistical and practical effect on academic outcomes of ACT achievement and graduation likelihood. In particular, Montana students from high poverty backgrounds have lower achievement on the ACT and are less likely to graduate compared to their peers from low poverty backgrounds. In particular, the intersection of students who are male and from high poverty experience compounded disadvantage on the academic outcomes of ACT achievement and graduation likelihood. As a direct result of challenging the normalized “achievement gap” policy and reporting in Montana, the need to better understand challenges and opportunities faced by male students from high poverty speaks to the need to expand policy and reporting away from explicitly Native and non-Native binary examination. Due to the current narrow focus of “achievement gap” work in Montana, we are likely missing awareness and supports needed around high poverty male students at large.

Another two-way interaction of significance is the intersection of AIAN and high poverty students on the academic outcome of ACT achievement. These intertwined challenges to academic success in Montana highlight the need to explore the sociohistorical contexts and systemic inequities that shape these students' experiences, shedding light on underlying opportunity gaps. In similar cadence to efforts of better understanding barriers and bias faced by

high poverty male students, future work needs to consider the unique challenges and opportunities faced by Native students in their journey to academic success, and in particular, Native students from high poverty should be handled as a group of students who have experienced compounded disadvantage where their distinct needs, supports, and experiences have a voice of their own.

Female students in Montana likely present a unique story of resilience in the face of navigating student and school-level barriers as seen in comparing the results of effect coding to the saturated models (and even looking ahead to the MLM models) by gender. Better understanding these stories and patterns of resilience—both in academic achievement and persistence—may help reveal important insight for practice. Not only would such insight assist in further supporting female students, but it may also reveal ways in which supports, mentors, and programs are lacking in assisting non-female students. Lastly, it is important to note that none of the three-way interactions or full expressions of social location were significant. Considering the limited statistical power of the disaggregated racial groups, future replication might consider aggregating students into fewer racial categories.

#### Within-Group Sample Descriptive Statistics

An unexpected finding in the formation of the Native student within-group sample is the substantial presence of Native students who lack an ACT score and also identify as English language learners (EL). Approximately 80 percent of EL students missing an ACT score in this study identify as Native, all of whom are naturally included in the within-group sample. This points to a need to consider the unique circumstances of Native EL students regarding their participation in standardized assessments in Montana. Under ESSA accountability provisions,

assessments of ELs are mandated, and Montana's Home Language Survey classifies Native Indigenous languages as a category of non-English language spoken across Montana households (OPI, 2018; 2022). This could imply two platforms for EL: 1) an Indigenous language is the primary language spoken in the home, and 2) students who face challenges in speaking, reading, writing, or understanding English to an extent that may prevent them from meeting state academic standards, succeeding in English-instructed classrooms, or fully participating in society (OPI, 2020b). Notably, since the release of Montana's Consolidated State Plan in 2018, fewer than 1 percent of Native students identified as ELs have achieved English proficiency (GEMS, 2023a). This raises concerns about both Native students' participation in state assessments and potential gaps in the EL identification process.

The testing of EL students involves several layers, including a screener assessment, an annual EL assessment for identified students, as well as the normalized standard assessments across all students. Resource-limited schools, such as rural on-reservation schools, may struggle to consistently screen and identify all EL students, potentially impacting these students' participation in standardized testing. The high proportion of Native EL students without an ACT score in this study could reflect these underlying obstacles. Additionally, the analysis may overlook EL students who have not been formally identified due to the absence of a screening assessment and are therefore missing from standardized testing entirely. Given that the data in this study overlaps with the timeframe of Montana's Consolidated State Plan release, future investigations into EL identification and standardized assessment participation should also examine more recent data to capture any changes in policy or practice. Further, the results of the robust logistic MLM analysis (model b) indicate that Native students who identify as former ELs

have the highest odds of successfully graduating compared to the other definitions of EL status. This finding suggests that early identification and support for EL students may positively impact educational attainment, underscoring the importance of these services for academic success.

Another unexpected finding in the descriptive statistics of the within-group sample is important to consider before exploring the interpretations and implications of research questions 3 and 4, as both these sets of models utilize mobility as the independent variable. Native students in Montana present a statistically significant relationship between mobility and reservation status, where in particular, Native students attending a school on-reservation experience less mobility than students off-reservation. In other words, Native students move between schools more when they attend schools that are geographically off reservation lands—largely removed from cultural norms and practices, and likely attending a school that predominantly serves white students with classes taught by white teachers. While this study faces limitation in interpreting much about this finding, future work should consider qualitative research that collects the narratives of Native students' experiences who are highly mobile attending schools off-reservation, or between schools on- and off-reservation.

Perhaps such stories would allude to aspects of school climate and lower sense of belonging at off-reservation schools. Sense of belonging is a theoretical antecedent to persistence (Hauseman et al., 2007; Hurtado et al., 2007; Walton & Cohen, 2007) where in turn, better understanding students' sense of belonging may provide insight to Native student persistence (Tachine et al., 2017). School belonging, generally defined by Libbey (2007) and later affirmed by Hattie (2009), is a conglomerate of both a feeling and a need influenced by the role of the teacher, individual engagement, and social influence: school belonging is when students “feel

close to, a part of, and happy at school; feel that teachers care about students and treat them fairly; get along with teachers and other students, and feel safe at school” (Libbey, 2007, pg. 52). This definition of school belonging is largely the relationships established and experienced within the school and learning environment, however sense of belonging in the school environment for Indigenous students is more nuanced. Indigenous students can feel a sense of alienation in mainstream schools as often these are schools lacking culturally responsive curriculum or where Indigenous students feel their cultural identity is not recognized or respected (Brayboy, 2005; Castagno & Brayboy, 2008), which certainly diminishes sense of belonging. Further, such schools in Montana are limited in offering peers and educators who share their Indigenous identity. As identified by a Native on-reservation educator, “our children need teachers who look and talk like them” (Clausen et al., 2020). The higher mobility of Native students in more mainstream, off-reservation schools in this study is perhaps due to grappling with belongingness. In comparison, Native students on-reservation are more likely to be surrounded by curriculum, peers, teachers, and practices that honor their Indigenous identity.

### RQ 3: Considering Opportunity Factors and Academic Achievement

Student Level Influence on ACT Achievement. The robust linear MLM analysis used to answer research question 3 reveals the majority of unexplained variance remains at the student level. While schools do contribute to shaping Native students’ performance on the ACT, the influence of individual differences are much stronger. In this way, school interventions focused only on improving resources or school environment will not fully address needs related to improving ACT scores among Native students. Rather, future research and choices in school practice need to also consider personal or student-level factors such as socioeconomic status,

motivation, family environment, etc. This overarching result reinforces a need to not strictly examine the school environment, but also individual and familial contexts in analyzing academic performance outcomes such as test scores. Familial contexts were largely left unexplored in this study, and perhaps offer the needed next area of investigation considering the influence of Native students' student-level characteristics on ACT achievement.

Reardon (2011) argues family socioeconomic characteristics such as income, parental educational attainment, family structure, neighborhood conditions, parental preferences etc. are primary determinants of academic achievement and educational attainment. Reardon's work even investigates the relationship between rising income inequality with a widening gap in achievement concluding the association between family income and achievement have grown stronger over time (2011). Perhaps this is in part attributed to how parents (particularly middle-class parents) have turned focus on children's cognitive development in recent decades (Schaub, 2010). Some studies have found parents with high educational attainment and higher-income spend more time in activities with their children than less educated and lower-income parents (Guryan et al., 2008; Ramey & Ramey, 2010). Further, the relationship between parents' educational attainment and family income has grown stronger in recent decades as these become generational patterns (Reardon, 2011). A future extension of this dissertation study should remove the school-level factors without significance (i.e. reservation status, Native student density, and rurality) and instead consider some variables of family socioeconomic characteristics such as parental income and educational attainment.

Student Mobility on ACT Achievement. Across all models, Native students who are not mobile have higher ACT scores than students who are mobile with statistical and practical

significance. This finding is in line with existing literature that high mobility is often associated with lower achievement (Rumberger, 2003). Given the significant role student mobility as an opportunity factor played in predicting ACT outcomes, future research should be two-fold: 1) Future research should explore mobility with more detail rather than as a binary variable. In particular, frequency of school enrollments and type of school moves (e.g. on to off reservation) should be considered. This study revealed mobility is a substantial predictor of academic achievement, future research needs to better understand the kinds of mobility and relationships to academic success. 2) Future research needs to better understand timing of moves within a student's educational experience, both across grades and within a single school year. For example, considering whether there is an age threshold when mobility between schools has more impact on academic outcomes, or if mobility after a certain point in the school year has more of an impact than within the first few weeks of a new school year. In practice, schools should consider implementing support systems for mobile students such as personalized academic counseling.

The linear analysis reveals that student-level factors significantly impact ACT achievement scores, indicating a need for future research to further investigate family socioeconomic characteristics as critical student-level influences. Notably, the prevalence of mobility's negative impact on ACT scores also underscores the importance of considering the family dynamics that contribute to this mobility. This study shows that Native students experiencing mobility have lower ACT scores and a decreased likelihood of graduating. This should be interpreted with caution, especially considering descriptive statistics of the within-group sample found on-reservation students are less mobile than off-reservation students. This

study overlooks the potential positive aspects of mobility within Native communities. Qualitative narratives, which were not captured here, could offer deeper insights into how Montana Native students navigate mobility, particularly within the context of Indigenous kinship structures that may influence students' movements between homes and schools. Lomawaima and McCarty (2006) highlight the strength of such kinship networks in Indigenous education, where for example, a child might live with an uncle to receive formal instruction in ceremonial roles. This study's focus on the challenges of mobility risks overlooking the cultural strength embedded in Indigenous educational practices, which view mobility not as a barrier, but as a form of resilience and community-based learning.

#### RQ 4: Considering Opportunity Factors and Academic Completion

School Level Influence on Graduation Likelihood. The robust logistic MLM analysis used to answer research question 4 reveals the majority of unexplained variance remains at the school level, suggesting that the school environment itself is a critical determinant of student success. While student characteristics do contribute to shaping Native students' likelihood to graduate, the influence of school differences are much stronger. In this way, school interventions focused only on the individual will not fully address needs related to academic completion among Native students. Rather, future research and choices in school practice need to also consider improving resources and school environment. Perhaps even pushing further, school choices such as bolstering tutoring, behavioral programs, or test readiness programs should not be considered interventions toward the school environment. While they are perhaps school-wide initiatives, these are student-level supports. Suggested here is the turn to considering and addressing deeper structural challenges Native students face.

Considering the importance of better understanding the structural aspects of the school environment's impact on Native students' academic completion, descriptive statistics of the within-group sample reveal an important finding: Native students who dropped out attended schools with an average school poverty slightly lower (more affluent) than students who graduated. This potentially suggests that while Native students who drop out may have access to greater school resources, these resources may not adequately address the barriers they face. Despite having support available, the obstacles to completing high school—whether socioeconomic, cultural, or systemic—may still be too significant to overcome. This highlights the need for more targeted, culturally responsive support systems that address the specific challenges Native students encounter, especially at off-reservation schools. Similar to the interpretations and implications surrounding greater mobility of off-reservation students, sense of belongingness might also be considered as a barrier to academic completion for Native students dropping out from more affluent schools—likely mainstream, off-reservation schools. Future qualitative research needs to better understand how belongingness—as an antecedent to persistence (Hauseman et al., 2007; Hurtado et al., 2007; Walton & Cohen, 2007) —impacts the academic experience of Native students attending off-reservation, mainstream schools where this study potentially alludes to more Native student mobility and dropout. In contrast, such a study should consider critiques of how sense of belonging relates to Native students. A fragmented sense of belonging—shaped by colonization and forced displacement that disrupted ancestral lands and cultural practices—may also impact Native students. As a result, Native students may struggle to maintain their identity within a predominantly non-Native learning environment (Kapisi et al., 2022).

This interpretation and implication are not to say on-reservation or high Native student density schools have equitable school environments. The disparities of school resources and quality of teaching are of significant concern in addressing school-level factors influencing Native student academic completion. In fact, model c of the robust logistic MLM reveals on-reservation students are overwhelmingly less likely to graduate compared to their peers in off-reservation schools when holding all else constant. In other words, on-reservation students face a dramatic disparity in graduation outcomes, even when other factors like school-level poverty and mobility are considered. Specifically, the odds of graduating for students attending schools on-reservation are reduced by approximately 99.95 percent. This calls for future research to investigate school-level influences such as teacher quality, teacher-student ratios, funding disparities, access to technology, etc. especially between on- and off-reservation schools. Furthermore, such findings need to be valued and acted upon by legislation and policy.

Perhaps one of the more substantial school-level impacts on equitable and quality education is access to good teachers. Research consistently reveals quality teachers as the most important resource for students in improving outcomes and access (Goldhaber 2015; Stronge et al. 2007). Schools in rural locations, and certainly rural on-reservation communities, face challenges in recruiting and retaining quality educators. These challenges include depressed salaries (Azano, Downey & Brenner, 2019; Biddle & Azano, 2016; Fink & Brayman, 2006), social isolation in rural communities (Biddle & Azano, 2016, Fink & Brayman, 2006) or professional distances (Azano et al., 2019), policy neglect (Corbett & White, 2014), technology access, health disparities, and poverty rates (Azano et al., 2019). Specifically at rural on-reservation locations, schools not only face challenges recruiting and retaining quality educators,

but educators with expertise in culturally responsive curriculum. In school environments with greater density of Native students, the importance of including Indigenous knowledge systems, worldviews and learning styles is rooted in more than relevance. Castagno and Brayboy (2008) argue traditional schooling can fail Indigenous students by overlooking cultural identities and values. Quality teachers for these student populations must be equipped in culturally responsive education.

Student Mobility on Graduation Likelihood. Across all models, Native students who are not mobile are more likely to graduate than students who are mobile with statistical and practical significance. This finding is in line with existing literature that high mobility is often associated with reduced academic attainment (Astone and McLanahan, 1994; Crowder & South, 2003; Ingersoll et al., 1989; McLanahan & Sandefur, 1994; South et al., 2007; Straits, 1987; Swanson & Schneider, 1999, Teachman et al., 1996; Welsh, 2018, 2017). This finding echoes the needs articulated previously of student mobility on ACT performance: Future research should explore frequency of school enrollments, types of school moves, and timing of mobility within the students' academic experience. Similarly, schools should consider implementing support systems for mobile students such as personalized academic counseling.

A unique consideration separate from the finding of student mobility on ACT performance is to align mobility at the crux of the two unique findings of the within-group sample descriptive statistics. If Native students attending schools off-reservation experience more mobility on average, and Native student dropouts attend more affluent schools (likely off-reservation) on average, then we may ponder the case of Native students attending schools off-reservation as more likely to experience mobility and to dropout. We know from model c of the

robust logistic MLM that on-reservation students face substantial barriers to academic completion. However, this unique group of Native students attending school off-reservation may also require additional investigation especially considering their mobility patterns (where and why they transfer schools) and sense of belonging on propensity and motivation to graduate.

Native Males At-Risk. The results of effect coding revealed that when considering gender in isolation, male students receive higher scores on the ACT and are more likely to graduate compared to their female student peers. However, in nearly all other model analysis of this study, this result is reversed when other factors are added, where Native female students have higher scores on the ACT and are more likely to graduate. As previously stated, this calls for further consideration of simultaneously the resilience of Native female students, as well as unique barriers and bias towards Native male students. This need to better understand the male student academic experience, particularly in the face barriers such as poverty and mobility, is accentuated further by the robust logistic MLM analysis (model b) where Native males are about 50 percent less likely to graduate compared to female students. Recall, model b holds constant EL status, student poverty and student mobility.

This may reflect that Native male students, especially from low socioeconomic backgrounds, face systemic biases in educational expectations and support structures where educators may perceive them as less academically capable (Auwarter & Aruguete, 2010), leading to lower expectations (Johnson, 2015), fewer opportunities for support and increased disengagement (Aydin & Ok, 2022). Both the work of future research and practical implications adopted by schools need to better understand such unique barriers for Native male students such as the potential of disciplinary biases, social pressures, or lack of tailored support. It is important

to note the results for Native male students remains unchanged for model c which adds school-level variables, suggesting that male students' lower likelihood of graduating compared to female students is robust across both student-level and school-level contexts. In other words, the gender gap in graduation among Native students is not influenced by the additional school-level factors of school poverty, Native student density, Title 1 status and rurality—reservation status the only exception. Knowing the majority of unexplained variance remains at the school-level for the robust logistic MLM analysis, a continuation of this study should consider other school-level factors which may be uniquely influencing male student academic success such as teacher perceptions and discipline or behavior data. Qualitative research should examine individual factors such as peer influences, family expectations, or potential bias in educational support systems among Native male students.

### RQ3 & RQ4 Summary

Across all models addressing research questions 3 and 4, student poverty has significant statistical and practical effect on academic outcomes of ACT achievement and graduation likelihood. In particular, Montana Native students attending school on-reservation and Native male students are two groups of students whose academic barriers are likely inextricably linked to poverty. The robust linear MLM analysis points to the need of better understanding student-level factors, such as family socioeconomic characteristics, and their impact on Native students' success on the ACT. While the robust logistic MLM analysis points to school-level factors, where the encouragement of this study is to focus on quality educators across all of Montana schools, and their impact on Native students' propensity to graduate. Here again, poverty is inextricably linked: Factors such as parents' income and educational attainment are wrapped in

common stories of poverty, and quality educators are more challenging to recruit and retain in higher poverty schools, such as rural on-reservation school communities.

Student mobility has consistent significant effects on academic success outcomes where students who remain in the same school throughout their high school experience achieve higher scores on the ACT and are more likely to graduate. The substantial impact of mobility on Native students' academic experience calls for further mobility research of Montana's students. Most generally, this call is to better understand mobility across all of Montana's students, rather than just the Native student sample. Continuing analysis of this study's within-group sample, future research needs to better weigh the unique relationships revealed in the descriptive statistics—namely that Native students on-reservation are less mobile than Native students off-reservation. Acknowledging “land is central to Indigenous identity... [though this] does not mean that Indigenous identity is geographically determined,” (Grande et al., 2015, pg. 111) the consideration for Native students' connectedness to the land (Kapisi et al., 2022) and the impact moving to a school off-reservation may have on “rootedness” (Grande et al., 2015, pg. 11) should inform such continued analysis. While the general findings of mobility's negative impact on Native student academic outcomes is in cadence with existing literature, the analysis through descriptive statistics highlights a need to utilize qualitative research to better understand the relationships Native students have with mobility: 1) Whether sense of belonging influences mobility, especially comparing belonging perceptions between on- and off-reservation schools, and 2) mobility as a positive relationship on the development of the Native student such as familial kinship structures. Ultimately, qualitative research would help uncover how mobility shapes Native students' experiences in different school settings.

### Impact of Student Poverty on Academic Outcomes

Across both the linear and logistic robust MLM analyses, student level poverty has statistical and practical significance on ACT scores and on propensity to graduate. In both approaches to analysis, student poverty plays a substantial role considering the inclusion of both student- and school-level factors. This perhaps suggests that student-level poverty has a multifaceted influence—affecting not only individual capabilities, but also how Native students engage within their school environments which potentially lack systems to support the unique needs of high poverty students. To be more specific, the findings of this study reveal Native students from low poverty tend to perform better on the ACT and are more likely to graduate, which may be due to increased access to educational resources, greater stability, and support systems. Such increased access contributes to the social, emotional and physiological development of children, especially for students living in poverty (Hewitt, 2011). Moreover, the influence on poverty is significant in these models even after controlling for student- and school-level factors, suggesting that economic disadvantage has a unique, compounding effect on educational attainment.

In this way, future research needs to better understand the impact and relationship of student-poverty on educational attainment across students. One extension of this study would be to examine the interaction of student mobility and student poverty, considering both variables consistently have a substantial impact on both types of academic outcomes examined here. If the interaction term is significant and negative as well, it would suggest the effects of mobility and poverty are not additive, but such students experience a compounded effect. In other words, students experiencing poverty and frequent school changes may face amplified disadvantage compared to a student who only faces one such barrier. This would support where the findings of

this study seem to be pointing, and where some literature already highlights, that mobility can exacerbate the challenges faced by students in environments of poverty due to disruptions in learning and their social stability (Rumberger, 2003). Such results of an interaction term would also reveal whether the negative effects of mobility are more pronounced for students in poverty. In turn, if the interaction is not significant, it may suggest that poverty and mobility independently influence academic outcomes.

Another avenue of future work would be to better understand the geographical context of Montana students' experiences with poverty. This study adds to the body of substantial literature supporting the reality that poverty is an educational inequity our students navigate. Schools, as the primary spaces where student navigate the academic journey, are placed at the intersections of space, power, and knowledge (Morrison et al., 2017; Soja, 2010) revealing unjust geographies of our school system. Both mobility and poverty are spatially informed opportunity factors. In this way, this study only reveals that both variables significantly impact academic success. However, a more complete understanding of how mobility and poverty impact Montana's students needs to also consider how these factors are situated spatially across geographic regions, school districts, and even on a binary comparison between rural and non-rural districts. Layering students and schools' experiences with mobility and poverty visually on a map would be a step toward better understanding structural and institutional relationships with power and place (Solórzano & Velez, 2016) in Montana.

### Recommendations

This study heeds the caution of Collins and Bilge (2016) that not all intersectional analyses are anchored in social justice. While this study aims to engage in such an intersectional

project to tell a more accurate story of “achievement gaps” in Montana, some may take these same findings and use it to justify or create structures for these marginalized groups. Therefore, as an overarching emphasis, the findings of this study should not be used for injustice, but rather to advance equity in education.

### Better Understand Female Student Resilience in Montana

Effect coding—when gender is considered in isolation with the study’s outcomes—found male students attain higher scores on the ACT and are more likely to graduate compared to female students. However, nearly all other models in this study revealed the reverse—that, with statistically significant results, female students score higher on the ACT and are more likely to graduate. In other words, when other factors influencing academic success are considered, female students are able to grapple with realities such as poverty or mobility, and despite these challenges, present a capacity to perform and persist higher than that of their male peers in similar circumstances. This reversal may point to a resilience in female students that needs to be better understood. Future qualitative research should explore the influences and stressors female students face surrounding their academic experience, further considering how these compare to that of male students and how they navigate these challenges and opportunities differently. In practice, schools might consider what supports and programs are in place and evaluate participation by gender. A student survey could gather primary stressors influencing male and female students as well as acted upon coping strategies. In addition, such a survey could further ask students to consider what school supports are available to them in navigating these stressors and level of accessibility. Considering the underlying reasons why females receive greater

benefit from such school support systems may reveal important dynamics of female resilience as well as pinpoint shortfalls in catering such support systems to non-female students.

### Highlight Barriers and Bias Faced by High-Poverty Male Students

One of the primary reasons this study asks the first two research questions and explores those answers through an intersectionality project is to disrupt the “achievement gap” dialogue in Montana. Currently, the literature, policy and reporting which surrounds “achievement gap” discourse in Montana focuses on a racial binary comparing Native and non-Native students. By only focusing on Native students and why they achieve at lower rates and drop out at higher rates, Montana risks neglecting other groups of students. By examining through the range of social locations, this study anticipated at least one other group outside of Native students would come forward. Both saturated models for academic achievement and academic completion revealed male students from high poverty backgrounds face barriers to academic success. Future research should seek to better understand these barriers. For example, quantitative research may provide valuable insight to patterns like the age range or grade level male students in high poverty tend to cross the threshold into higher risk. Qualitative research both with students and educators may articulate the experience of barriers such as implicit bias in the classroom.

Echoing the larger sentiment of this dissertation project, this finding calls for policy in Montana to expand from racially defined “achievement gap” reporting. Continuing to understand Native student experience and performance is mandated by legislation, and in turn provides needed and substantial funding to most of Montana’s high Native density schools. However, as seen in the results for high poverty male students, Montana’s narrow focus has produced racial bias in policy and reporting due to lack of considering disparities in academic success for all

Montana's students. Rather than producing the biennial and stagnant *American Indian Student Achievement report* which only compares Native students to their non-Native peers, Montana should reimagine reporting. For example, Washington's Statewide Longitudinal Data System produces an interactive dashboard affording the inquirer to select identities of intersectional social locations<sup>6</sup>. Montana could easily replicate an interactive dashboard which displays academic success outcomes such as standardized testing results and graduation rates by social location attributes including gender, poverty, English Learner status, etc. to further supplement current "achievement gap" reporting.

Montana would benefit from broadening its reporting standards across student groups; however, it is essential to recognize this study's finding that Native male students are approximately 50 percent less likely to graduate than their female peers. The awareness of academic experience, access and success of Native male students—particularly those from low socioeconomic backgrounds and on-reservation settings—is of prominent concern. Future research, particularly qualitative studies, should aim to capture the experiences of Native male students and the unique barriers they face, including peer influences, family expectations, potential biases within the education system, and limited access to role models and mentors. In practice, schools must prioritize the needs of Native male students with intentional and urgent support. Schools might consider interventions focused on factors they can most directly influence, such as educators' perceptions. Addressing any implicit biases educators may hold toward Native male students, both on- and off-reservations, is a necessary step, even though it requires sensitivity and thoughtful engagement. Establishing school-wide practices that foster

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<sup>6</sup> Explore Washington's dashboard via the link provided and selecting "intersectional groups" in the top menu: <https://erdc.wa.gov/data-dashboards/dual-credit-dashboard>

culturally responsive and supportive environments— such environments that recognize Indigenous identity as relational to both the self and the Indigenous community (Grande et al., 2015)—could make a meaningful impact, helping to counteract the compounded barriers Native male students encounter on their academic journeys.

### Consider ACT Achievement as a Generational Experience

The robust linear MLM analysis reveals that most unexplained variance in ACT scores exists at the student level, underscoring the importance of considering how family socioeconomic factors influence academic performance. Future research should investigate how family dynamics—especially socioeconomic characteristics—affect students' access to academic achievement. If findings indicate that family factors play a substantial role, educational policies at the school and state levels could address these challenges by focusing on the family unit and the generational nature of academic achievement. Montana should prioritize early childhood education, expanding affordable early-start programs and establishing a state-supported public pre-school system. These initiatives would ensure that children from low-income families, including Native communities, have equitable opportunities to develop strong educational foundations. On the other end of the educational spectrum, post-secondary institutions should offer additional support to first- and second-generation college students, providing pathways to success for students whose families may lack direct experience with higher education. Throughout a student's academic journey, schools should actively involve the entire family—including siblings and parents—in fostering the student's success.

Montana's current "achievement gap" reporting often frames performance disparities between Native and non-Native students as an issue inherent to Native students themselves,

perpetuating a deficit narrative. The fact that the majority of the unexplained variance is found at the student level should not lead us to conclude that Native students' personal characteristics are the primary determinants of their academic outcomes. A student-deficit approach is insufficient for promoting meaningful access and opportunity. Instead, this finding should prompt a deeper examination of the generational and systemic barriers faced by Native students and their families. Schools and policy makers must acknowledge the resilience these students exhibit in navigating systemic challenges and design educational initiatives that not only address these barriers but also honor and uplift the strength within Native communities. By reshaping the narrative around achievement, we can move beyond gaps in test scores to create equitable and culturally sustaining educational environments.

#### Focus on Quality Educators as a School-Level Response

Partnered with remote placement and significantly less salaries, many rural schools face recruitment and retention obstacles, perhaps serving as the "rural school problem" (Biddle & Azano, 2016) where the "problem" is not of rural school deficit (Azano et al., 2019) but rather that of the system. In Montana, Versland (2013) highlights the especially challenging reality of recruitment and retention for rural communities where applicants are offered a less handsome salary compared to non-rural institutions, often face challenges in accessing mentorship opportunities and resources, and must navigate geographic isolation. In addition, such rural educators must embrace a broad adaptability skill set to take on multiple responsibilities and roles (Versland, 2013). Further, in rural high Native density school communities, a quality educator must also be versed in culturally responsive schooling (Castagno & Brayboy, 2008). Despite the plethora of challenges Montana faces with retaining such quality educators in rural

on-reservation schools, they may serve as a defining factor in addressing school-level and structural inequity seen in academic success outcomes of its students.

The General Appropriations Act of 2021 (HB 2), which was effective July 1, 2021, passed a Montana “grow your own” program through the legislature. As part of the Commissioner of Higher Education general funds, the Montana Grow Your Own Teacher Grant Program functions as a collective state education system approach to strengthen the teacher pipeline. The effort recognizes that rural schools, and Native-dense community schools in particular, consistently battle recruitment and retention of educators. In this way, providing a state developed “grow your own” program combats teacher shortages through support efforts to provide these communities with licensed educators that are from and of these same communities. It is the continuation of such efforts, such as the continued establishment of 2+2 programs through Montana State University, that reshape the system. Montana must seek to continue support of such legislative grants and efforts by post-secondary institutions. We must ensure all students in Montana have access to quality teachers as we cannot afford to compromise such a fundamental need of all students.

#### Prioritize Native English Language Learner Students

The proportion of Native students, especially English language learner (EL) students, missing an ACT score in this study is alarming. The Montana Office of Public Instruction should consider further supplemental recourses, support and on-site training to schools of students’ completion of the English language learner screener exam. Access to language education is a civil rights issue, and providing the screener assessment is a requirement of the U.S. Department of Education—that school districts utilize a valid and reliable test that assesses English language

proficiency across speaking, listening, reading and writing. Furthermore, schools should prioritize raising awareness among educators and parents about what it means to be an EL student. Many people mistakenly assume that EL students are only those whose primary language is not English. While students with a primary language other than English do meet the criteria for EL designation, this definition is not exhaustive. English learners include students who face challenges in speaking, reading, writing, or understanding English to an extent that may prevent them from meeting state academic standards, succeeding in English-instructed classrooms, or fully participating in society (OPI, 2020b). By broadening understanding of which students may qualify as potential ELs and by assisting schools in accurately identifying these students, Montana can better ensure that the appropriate supports are provided to those who would benefit. The finding of the robust logistic MLM analysis (model b) indicating that Native students who identify as former ELs have the highest odds of successfully graduating across EL status definitions, suggests that the benefits of receiving such supports positively impact educational attainment.

#### Use Data to Support Mobile Student Populations

Not only do we need quality educators in all Montana schools, but Montana also needs to supply these educators with effective tools. Student mobility was a significant predictor across analysis for both academic achievement and academic completion. Montana should consider bolstering supports for mobile students, specifically Native students experiencing mobility, their teachers, and their counselors. By utilizing tools like an early warning system, which often track mobility as a predictor of at-risk likelihood, schools will be better equipped to not only identify students' whose mobility experience is having a negative effect on their academic success, but to

equip the school where the student transfers to. Tools like early warning systems produce reports that can be sent with a student when they transfer. If the state of Montana were to adopt state-wide use of such a tool, regardless of where the student transferred, they would come with a portfolio the next school could use for making informed decisions of how to best support that student such as yearly trends and previous interventions implemented. Such state-wide adoption would require only training and implementation across school teams. Currently, Montana's K-12 schools have access to the locally grown Montana Early Warning System of the Montana Statewide Longitudinal Data System program, as well as early warning systems offered by the two prominent school information system in the state: PowerSchool and Infinite Campus. Montana teachers and school teams have access to the data, we simply need uniform efforts of training to utilize such data to support scenarios (i.e. mobile students).

#### Align Qualitative Research: Native Students & Mobility

It is clear this study reveals a negative relationship between Native student academic outcomes and mobility, or in other words, the Native students in this study are more likely to experience positive outcomes on standard metrics of academic success when they remain in the same school throughout their high school experience. It is also revealed through the descriptive statistics analysis that Native students located at on-reservation schools have lower mobility than Native students attending schools off-reservation. Such findings and nuances make a case for collecting the narratives of students to better understand experiences with mobility (e.g. sense of belongingness off- versus on-reservation, mobility as a positive outcome such as kinship structures, etc.) before making the uninformed conclusion that Native students are more mobile than their non-Native peers and this is contributing to the gaps in academic performance between

these student groups. Rather, the relational and spatial narratives of Native student mobility will offer the most insight to the complexity of mobility as an opportunity factor.

### Build Geospatially Informed Visuals: Mobility & Poverty

This study found both mobility and poverty are substantial predictors of academic success outcomes across models, where students experiencing mobility, and similarly students from high poverty, achieve lower rates on the ACT and are more likely to dropout. Montana's Statewide Longitudinal Data System (SLDS) at the Office of Public Instruction could seek to present geographical context of poverty and mobility by replicating the work of Rhode Island's SLDS. A more recent project by Rhode Island's team was to create an interactive dashboard which presents chronic absenteeism on a map of the state, dividing out school districts by census tract and block group levels. Through this dashboard<sup>7</sup>, inquirers can examine correlations between student demographic characteristics and absenteeism outcomes, as well as achievement and absenteeism. Montana's SLDS could build a similar interactive map dashboard to further supplement current "achievement gap" reporting. In this way, the dashboard could present standard metrics for academic achievement (i.e. standardized test scores and graduation rates) on a map of Montana divided into its school districts. The user could then layer on filters of demographic characteristics including student poverty, as well as a filter for student mobility averages. In theory, the map would reveal districts where student mobility averages are the highest and where student characteristics such as poverty are most concentrated. Such a map could identify geographic regions which experience the most compounded effect. Further, it

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<sup>7</sup> The Rhode Island interactive SLDS dashboard can be explored on their website: <https://datacenter.ride.ri.gov/Home/FileDetail?fileid=1041>

would provide legislature and policy holders with an accessible visual tool to inform decisions around funding and other supports.

### Concluding Remarks

This dissertation project was in many ways a call to response following a qualitative study project (Clausen et al., 2020) I participated in five years prior. In this study, the mobility of Native students in Montana impacting academic success was a common theme expressed by parents, educators, and students from Native communities. In the years following and in my time at the Montana Office of Public Instruction, I came to realize we know very little about the relationships Montana's students have with mobility. This is in part due to how this data is collected—or not collected—at the state level where mobility patterns are left to be interpreted through school enrollments. There are many characteristics of mobility such as frequency or situatedness in the time of year that is left unacknowledged through this study simply due to the nature of the enrollment data currently collected. There are also contextual aspects of mobility, some of which are suggested in the recommendations of this study such as considering the positive influence of mobility among Native students as a product of moving due to kinship structures. However, there are also contextual aspects of mobility not referenced in this study, such as within districts moves (e.g. a student has a new school enrollment after the family moves across town), out of state moves, mobility influenced by negative home environment or characteristics (e.g. parent is incarcerated), mobility influenced by negative school environment or characteristics (e.g. student changes school due to bullying), or external influences on mobility (e.g. military mobility). Needless to say, between inspiration from the call of stakeholders in Native communities and bolstered by my own realizations of the lack around mobility data in

Montana, I feel summoned to begin filling the void of mobility's influence, relationship, and impact on students' academic journey in Montana.

I am greatly cautious that the results of this dissertation project will stamp mobility of Native students as one that has a negative relationship with academic outcomes. While yes, the results of this study reveal mobility negatively impacts performance on the ACT and propensity to graduate, I hope I have also illustrated that understanding mobility is much more nuanced. This study has confirmed both quantitative and qualitative data are needed to unearth the role and relationship mobility has in Montana. I strongly feel labeling mobility as an *opportunity factor* is the correct approach. Opportunity factors could be those that present a great barrier or challenge to opportunities of academic success (i.e. poverty), but they could also be more closely in line to their namesake: the influence of a positive opportunity for a student (e.g. mobility to a more stable home environment). I also strongly feel that capturing mobility as an opportunity factor requires both quantitative and qualitative means. As demonstrated by this study, a quantitative approach does not encompass mobility in its whole form.

I have presented mobility and poverty as opportunity factors to help Montana re-evaluate its approach to "achievement gaps." This centers on Native students as the Montana "achievement gap" is a racial binary of Native to non-Native comparison. This study has revealed both opportunity factors of mobility and poverty are substantial influences on Native students' opportunity to succeed. In this way, I feel this project has opened another door that would benefit Montana in re-evaluating how we capture and define the success of Native students. If we continue to only look at disparities in test scores and graduation rates, we do our students a disservice. I call for two major reforms: 1) We need to rethink how we define success,

especially for Native students. Success is not a singular test score. 2) We need to consider the wide array of barriers and opportunities our students face, especially Native students, perhaps beginning with a single variable such as poverty or mobility. Policy that neglects weaving the structural and systemic obstacles our students navigate passively ignores (perhaps with ignorance) the existence of oppressive systems, racism and inequity. Committed to progress through social justice intentions, the work of redefining “achievement gaps” pursues an outcome of educational justice for all students. This dissertation project has served as a platform for me to consider how my research might align; it has been a privilege.

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APPENDIX

DETAILED FIGURES FROM ANALYSIS

Figure 1.  
Density Plot for ACT Composite Scores prior to Mean Replacement

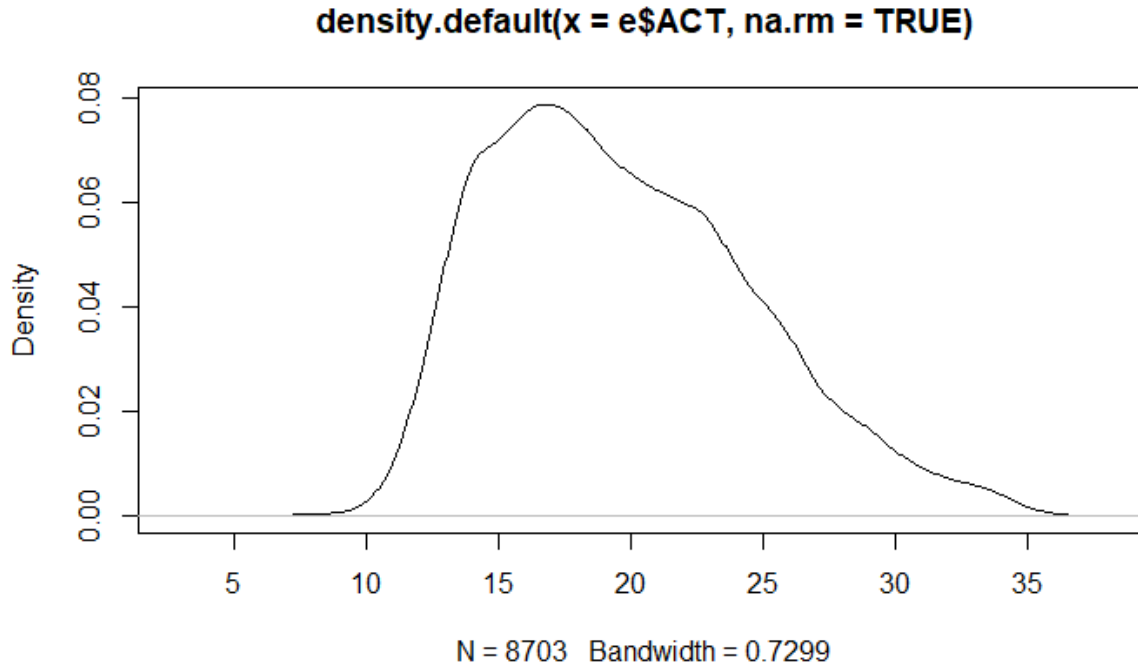


Figure 2.  
Density Plot for ACT Composite Scores after Mean Replacement

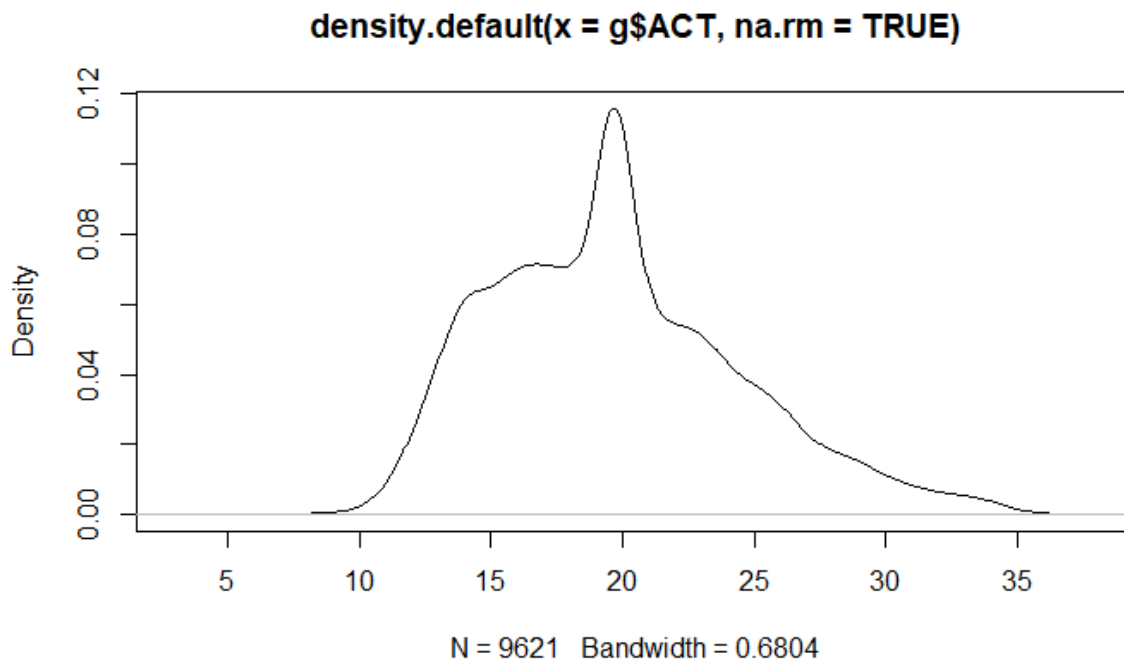


Figure 3.

Density Plot of ACT Scores After Multiple Imputation

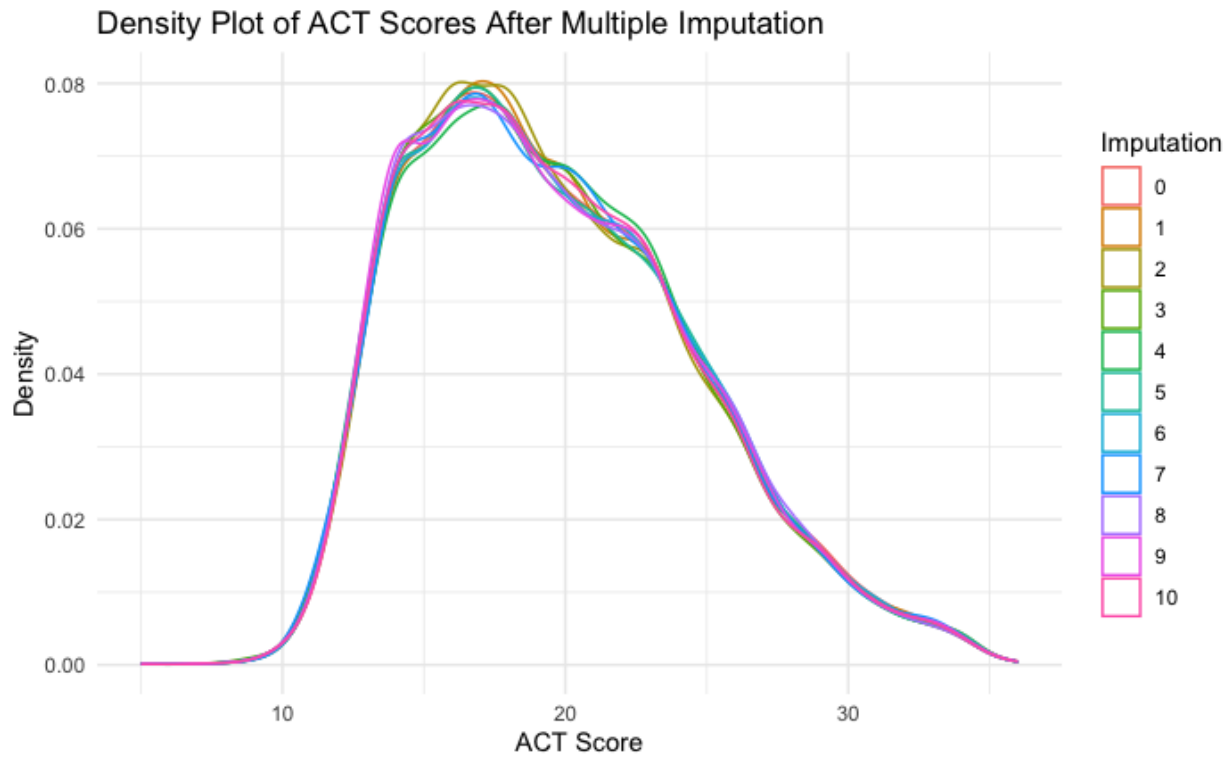


Figure 4.

Density Plot for School Poverty

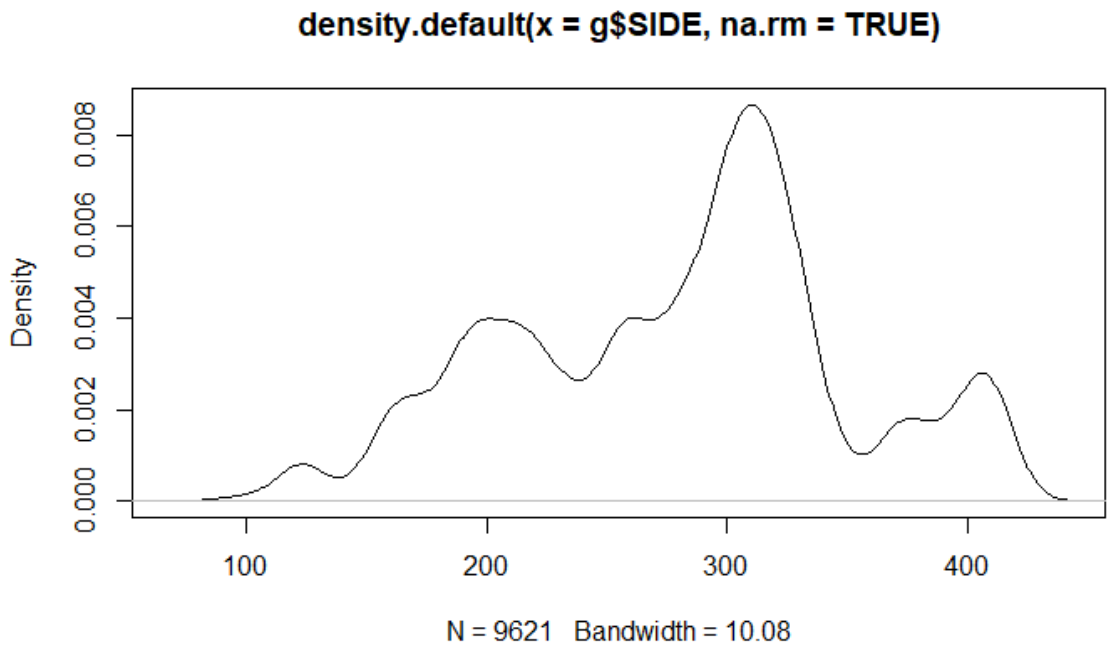


Figure 5.  
Correlation Between Academic Achievement (ACT) and School Poverty

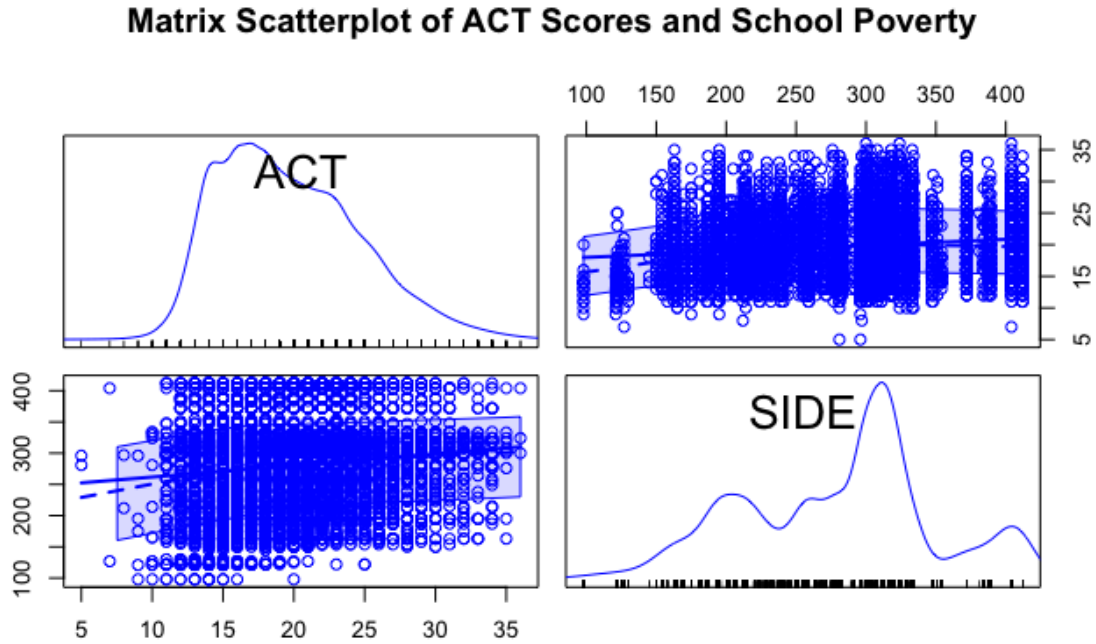


Figure 6.  
Boxplot of School Poverty by End Status

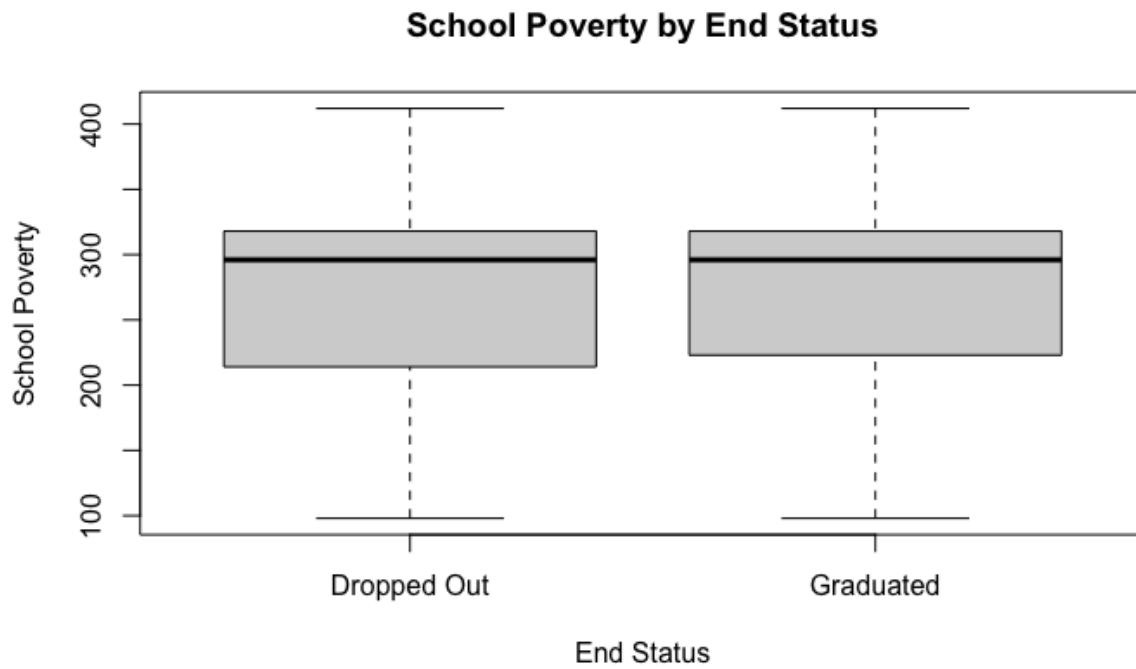


Figure 7.  
Density Plot for Mobility

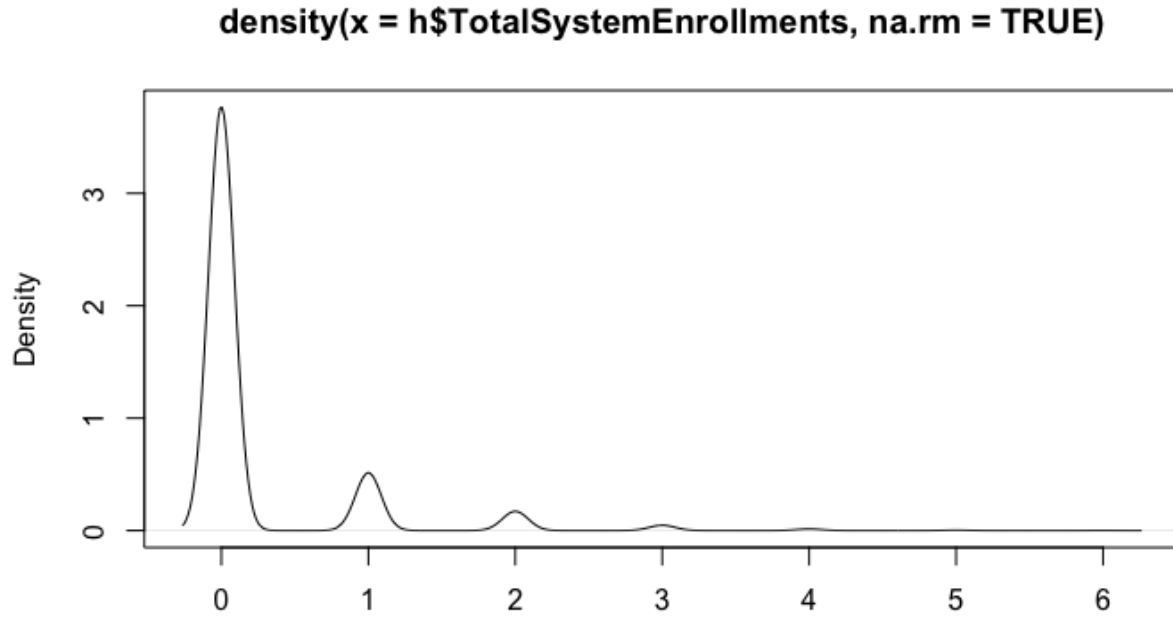


Figure 8.  
Boxplot of ACT Score by Mobility

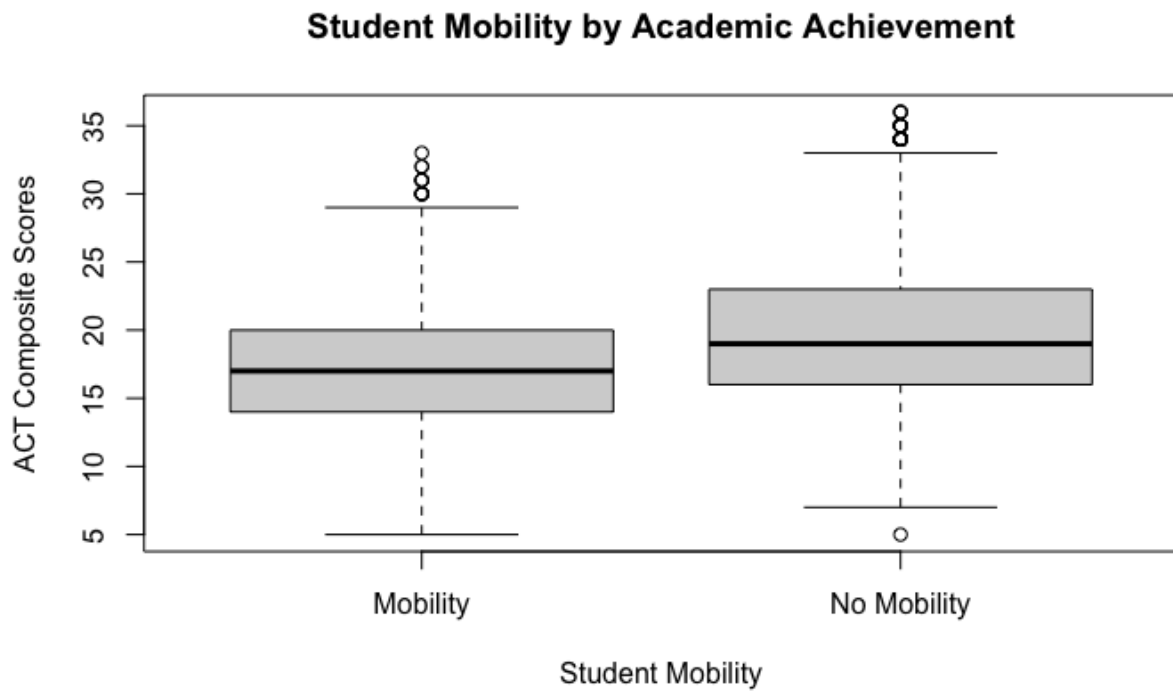


Figure 9.  
Boxplot of School Poverty IPR Values by Mobility

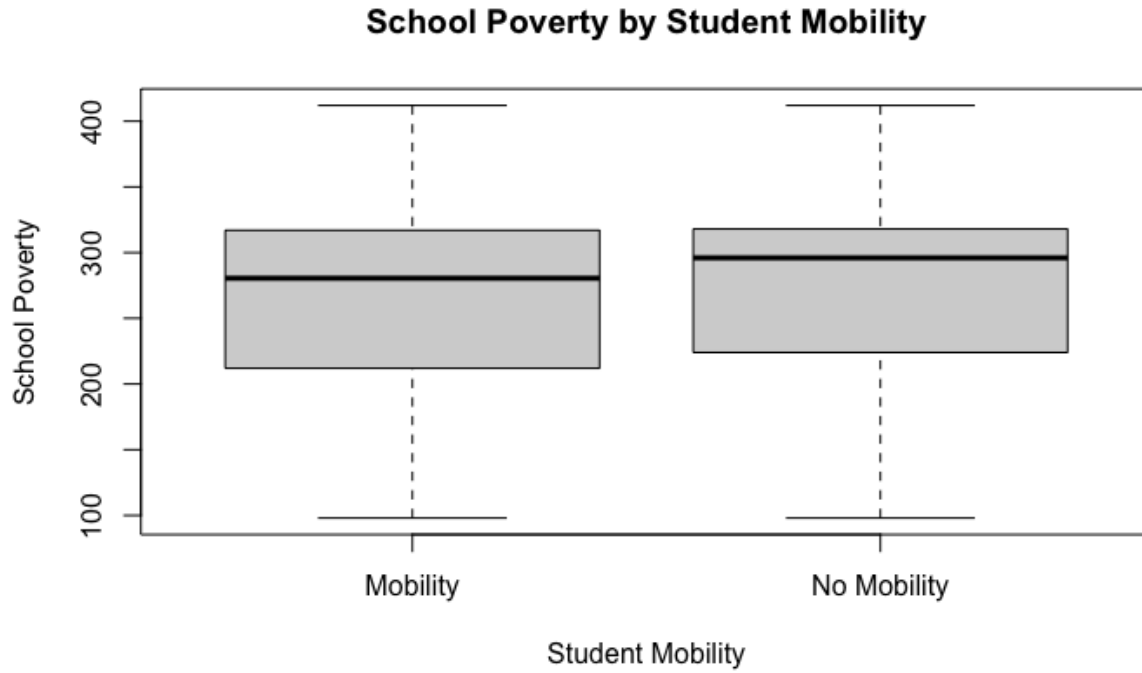


Figure 10.  
Boxplot of ACT Score by Race

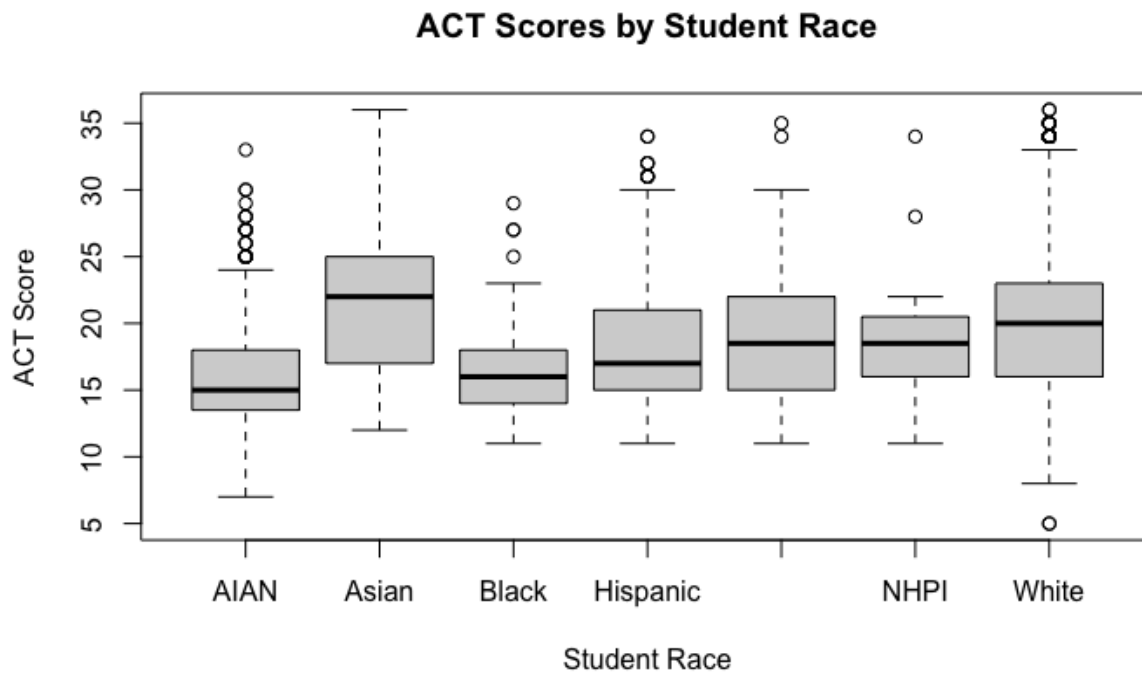


Figure 11.  
Boxplot of ACT Scores by Gender

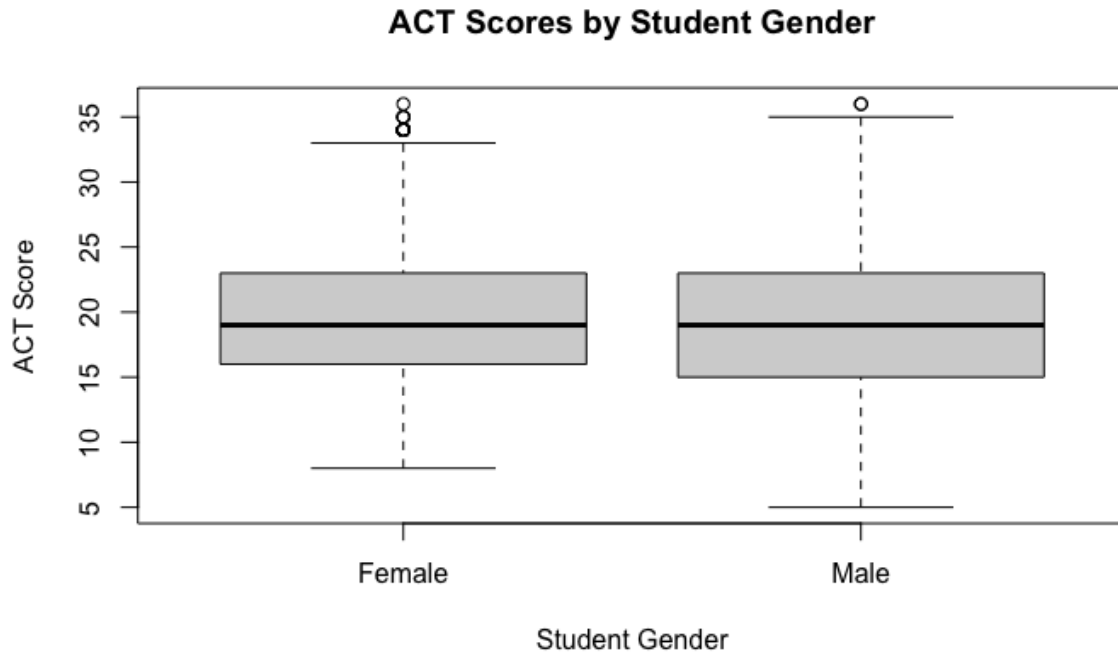


Figure 12.  
Boxplot of ACT Scores by English Learner Status

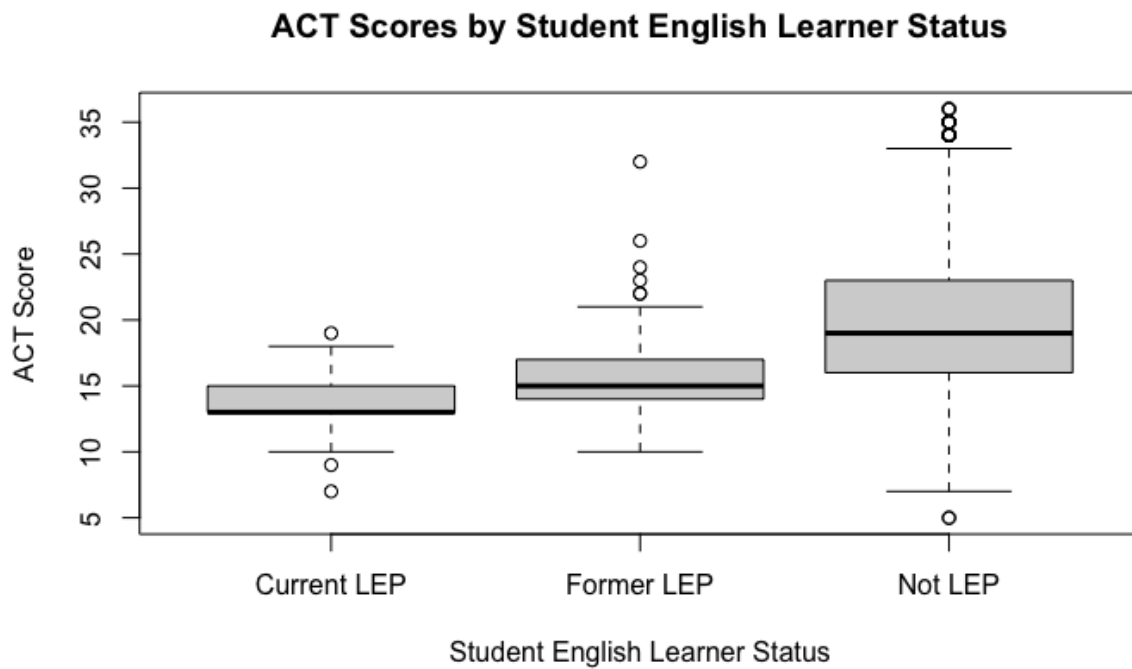


Figure 13.

Mosaic Plot of School's Reservation Status by Native Student Density  
 Schools' Reservation Status by Native Student Density

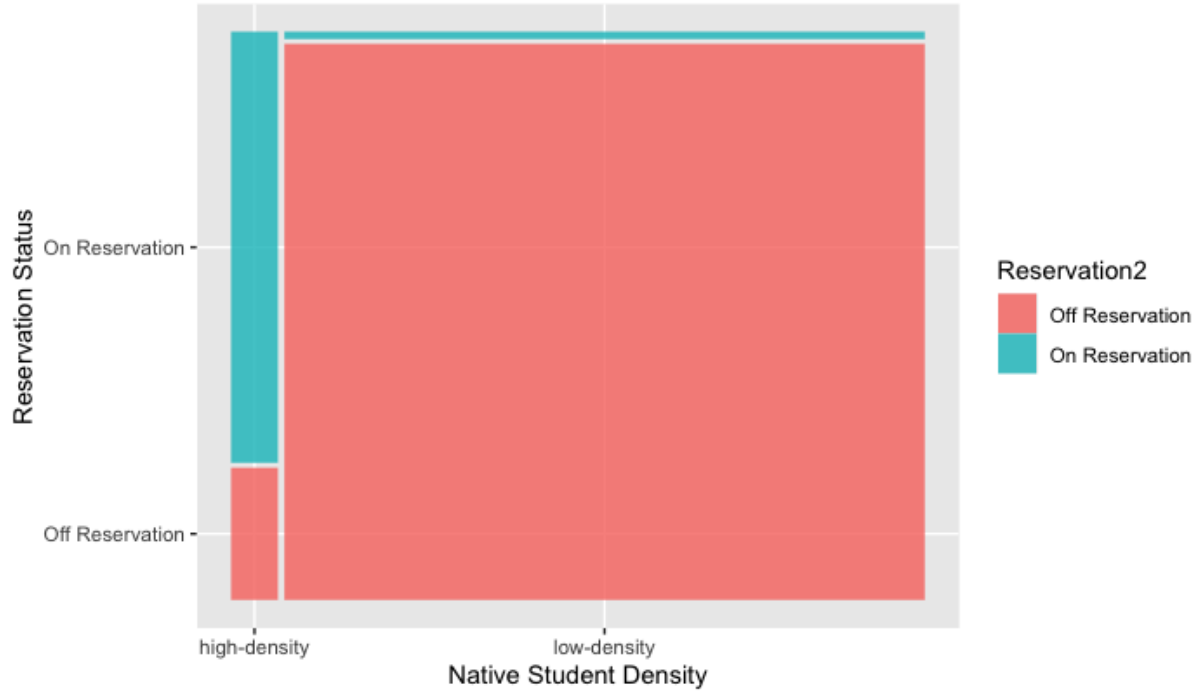


Figure 14.

Boxplot of ACT Scores by School Rurality

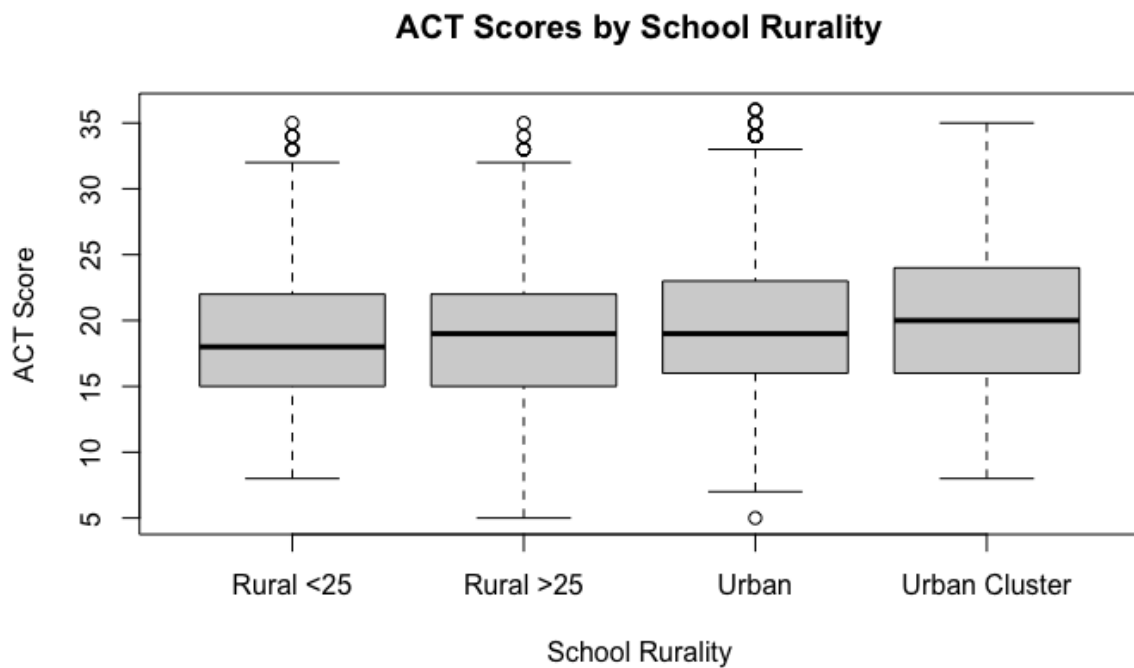


Figure 15.  
Boxplot of ACT Scores by Reservation Status

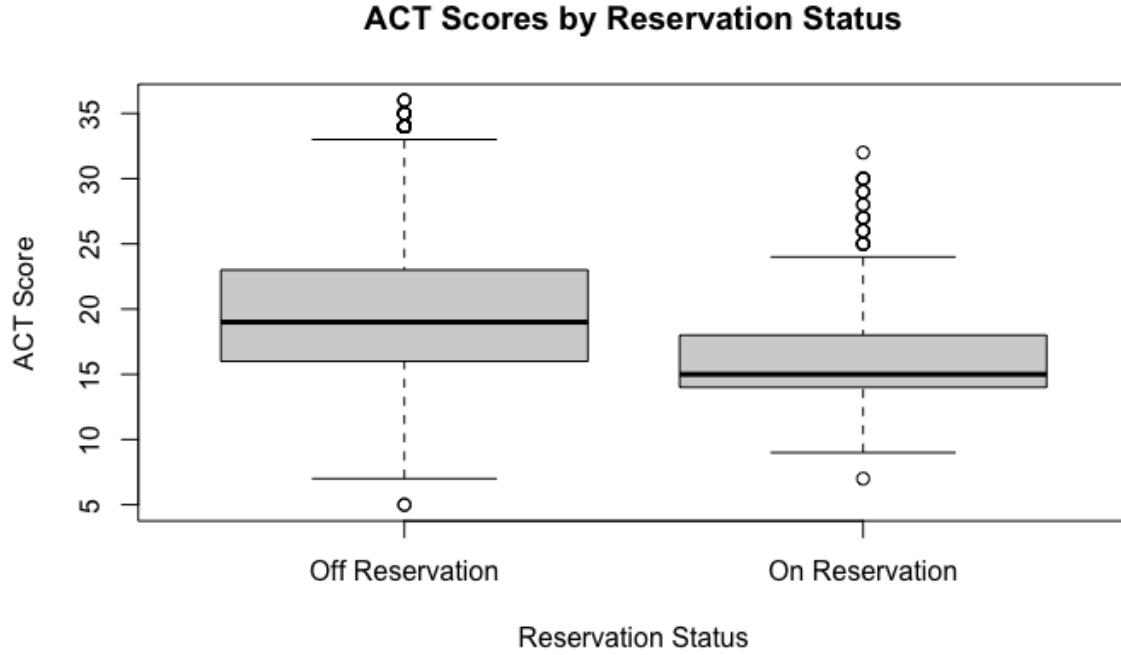


Figure 16.  
Scatterplot of School Poverty by Reservation Status (Red = On Reservation)

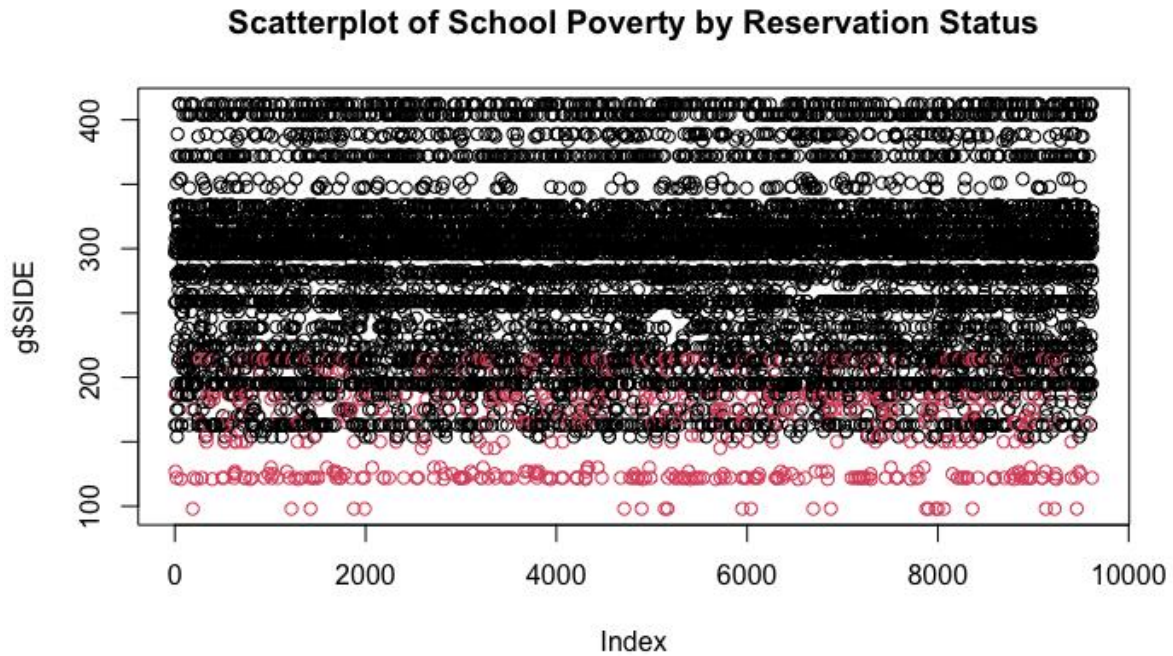


Figure 17.  
Boxplot of School Poverty by Reservation Status

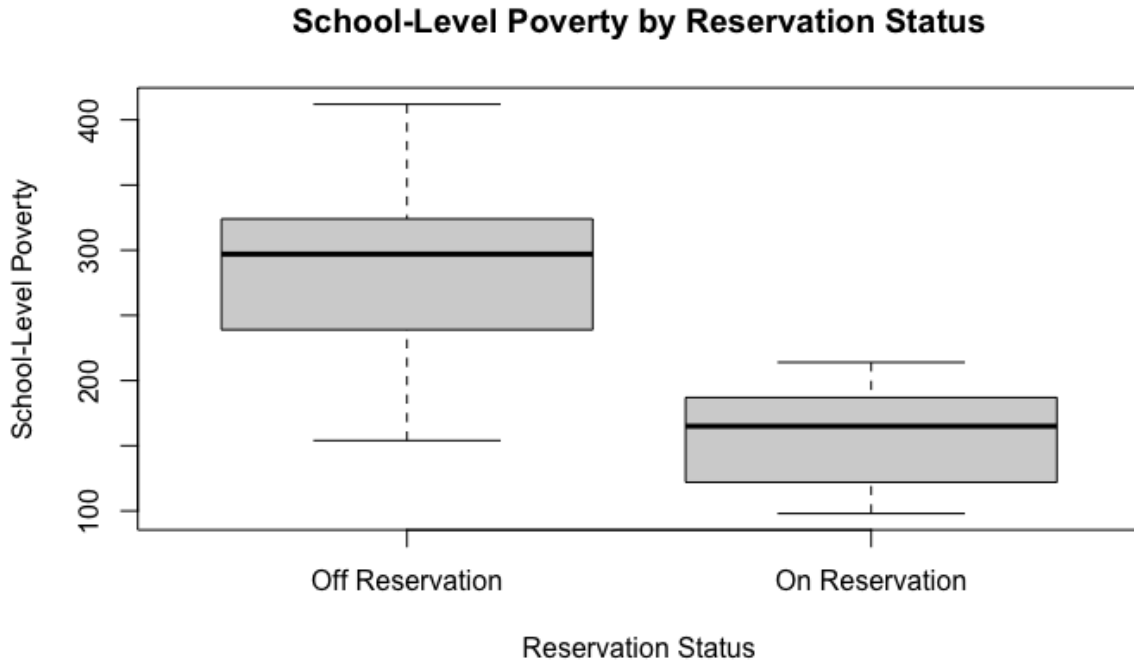


Figure 18.  
Boxplot of ACT Scores by Native Student Density

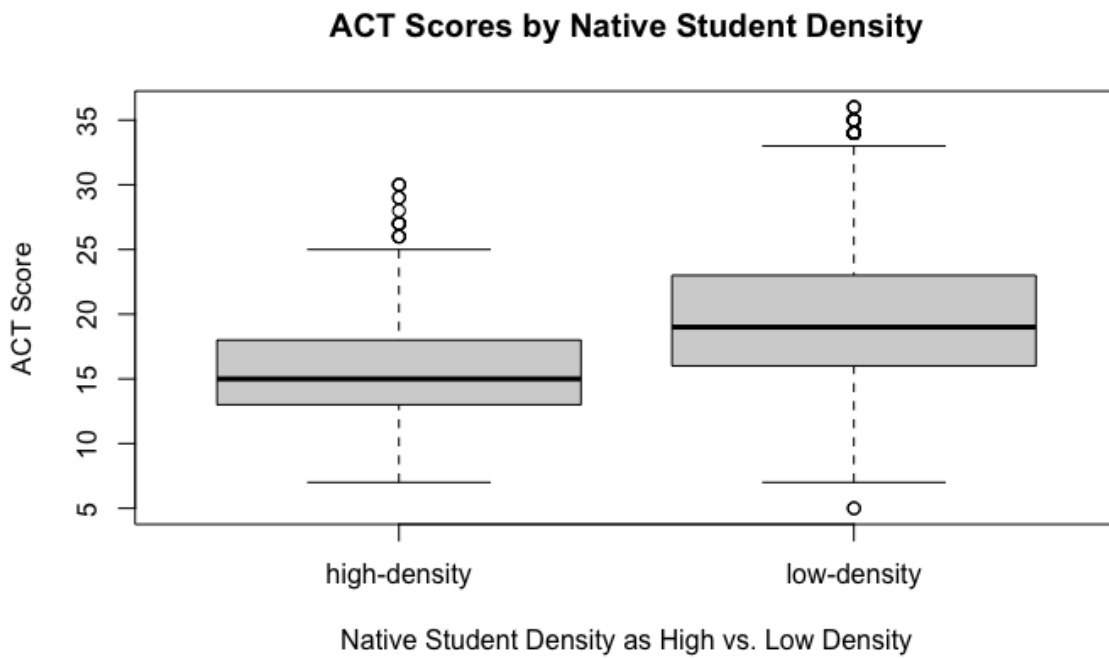


Figure 19.  
Boxplot of ACT Scores by Title 1 Status

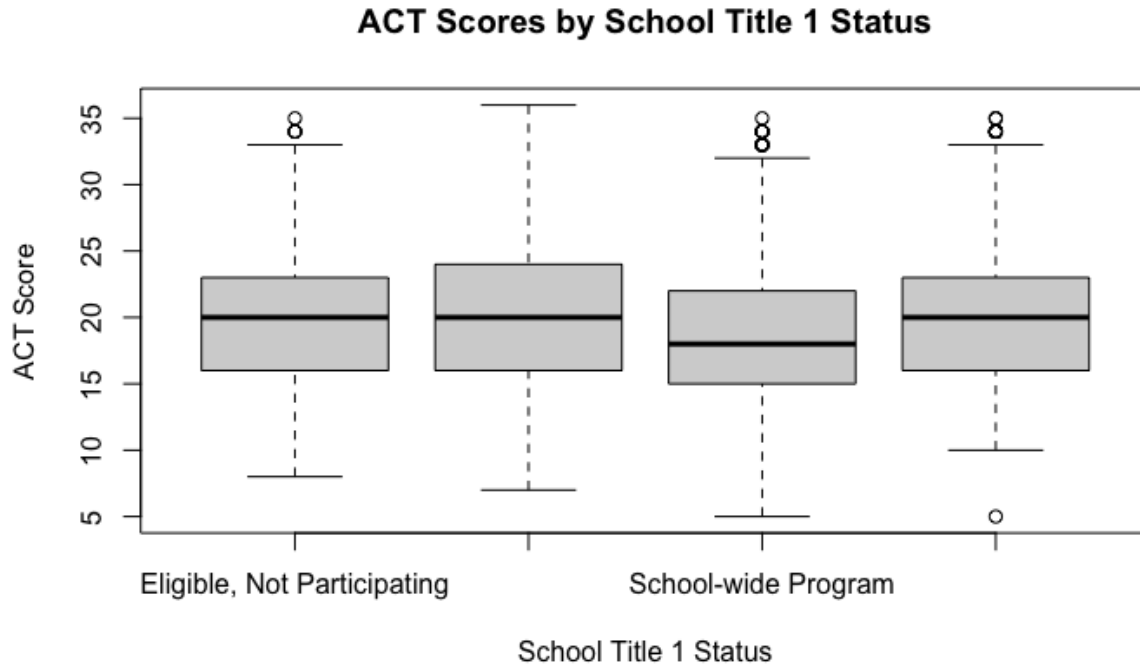


Figure 20.  
Comparison of Within-Group Sample ACT Density Plots Before and After Log Transformation

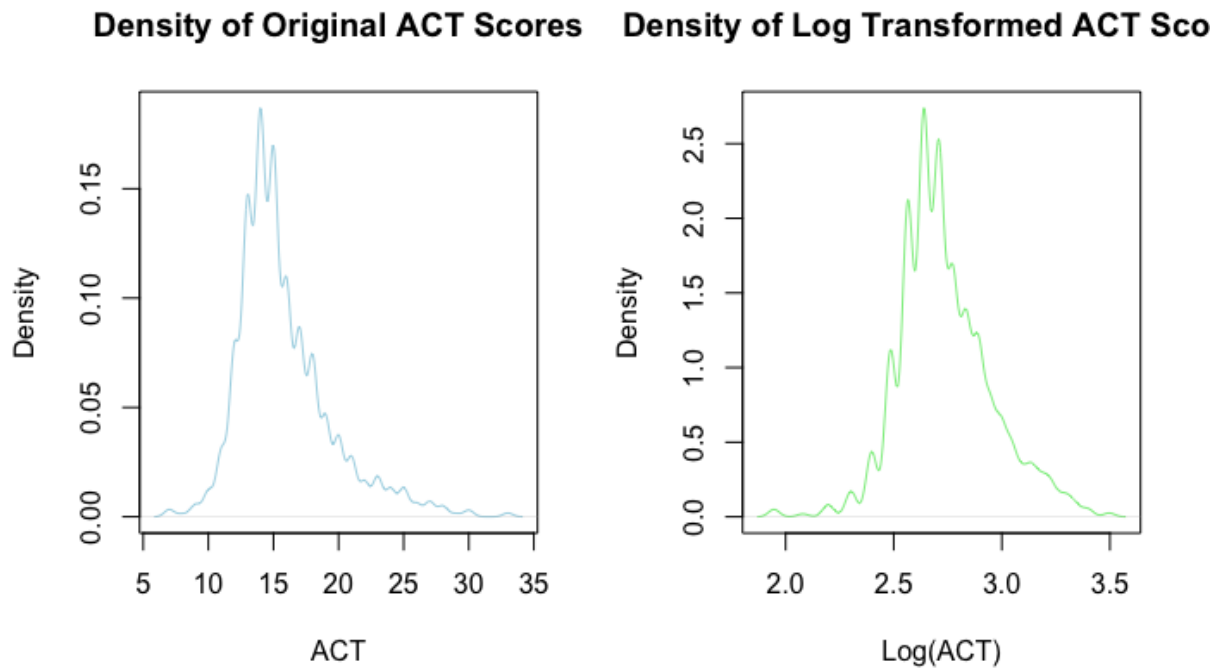


Figure 21.  
Comparison of Within-Group Sample ACT QQ Plots Before and After Log Transformation

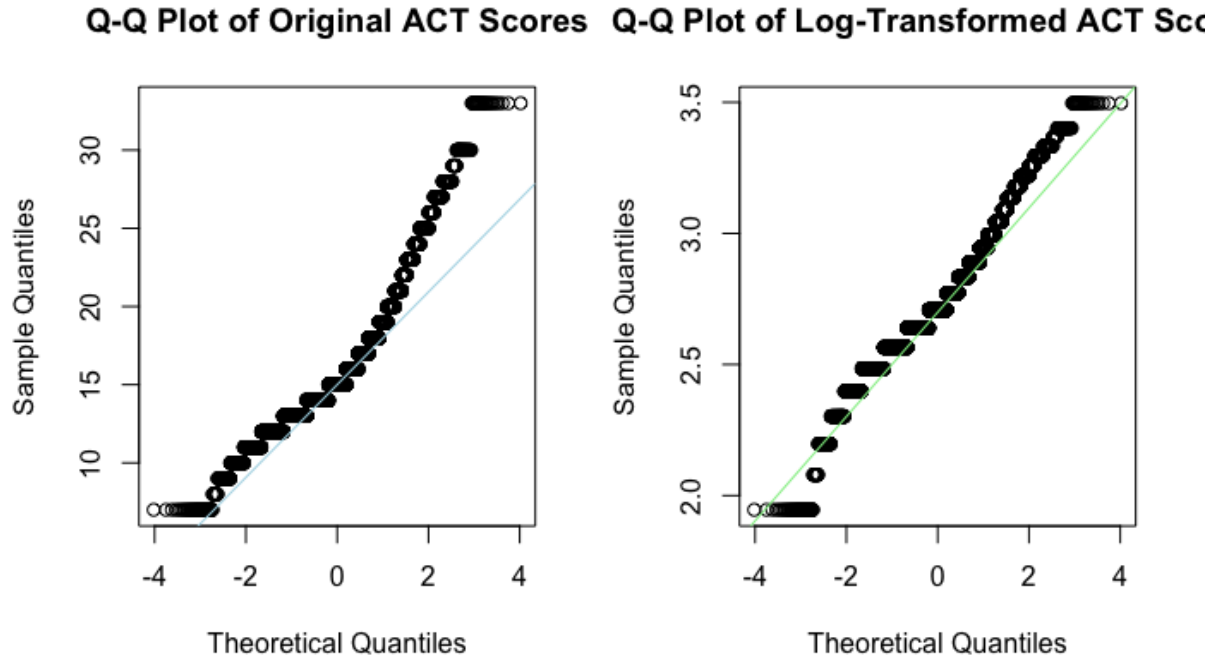


Figure 22.  
Boxplot of ACT Score by Reservation Status

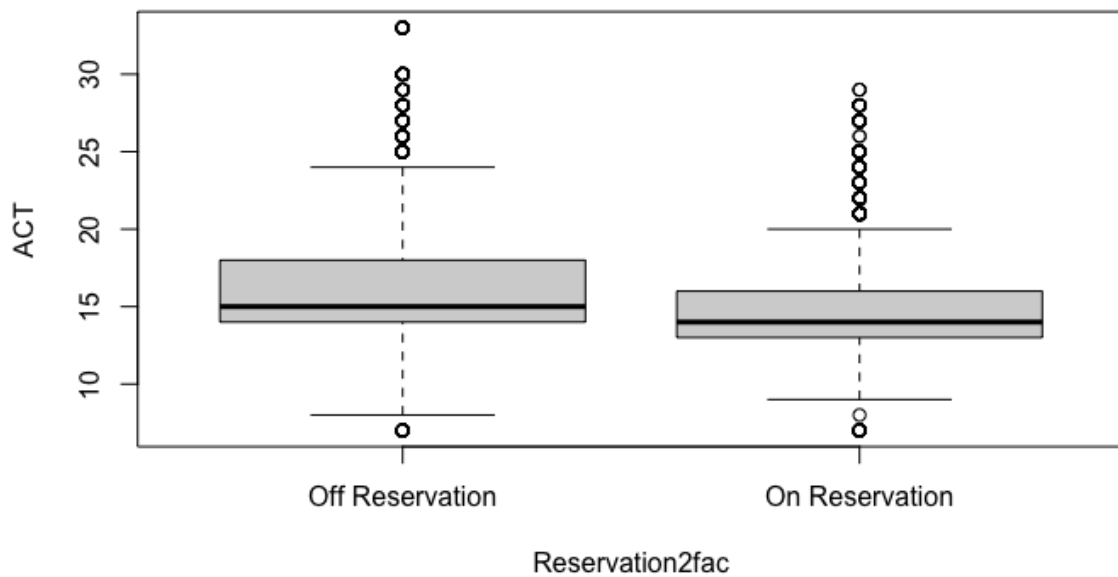


Figure 23.  
Boxplot of ACT Score by Binary Native Student Density Status

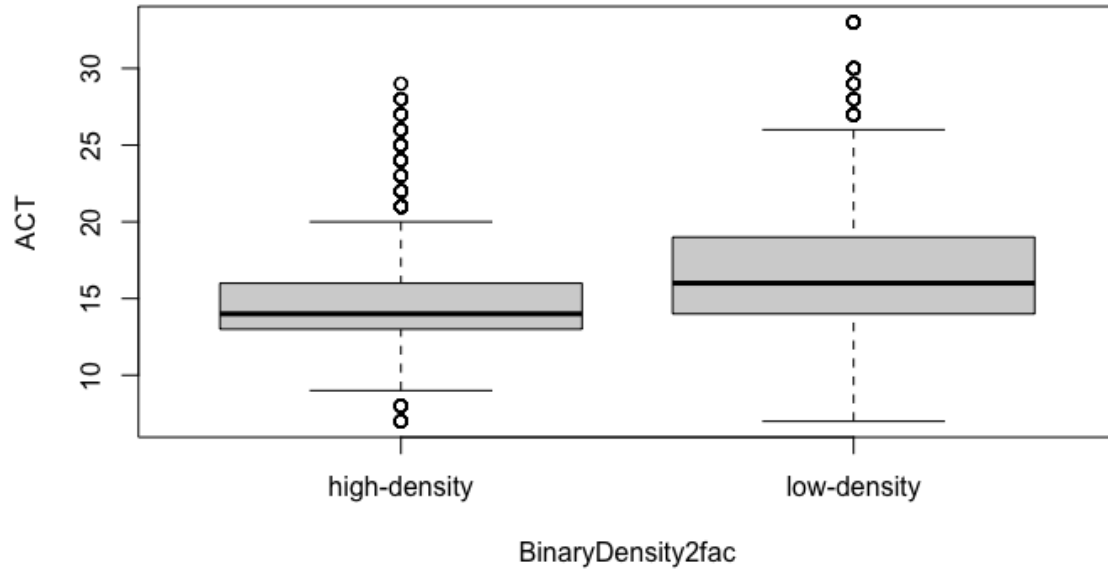


Figure 24.  
Within-Group Sample School Poverty and ACT Score Scatterplot Matrix

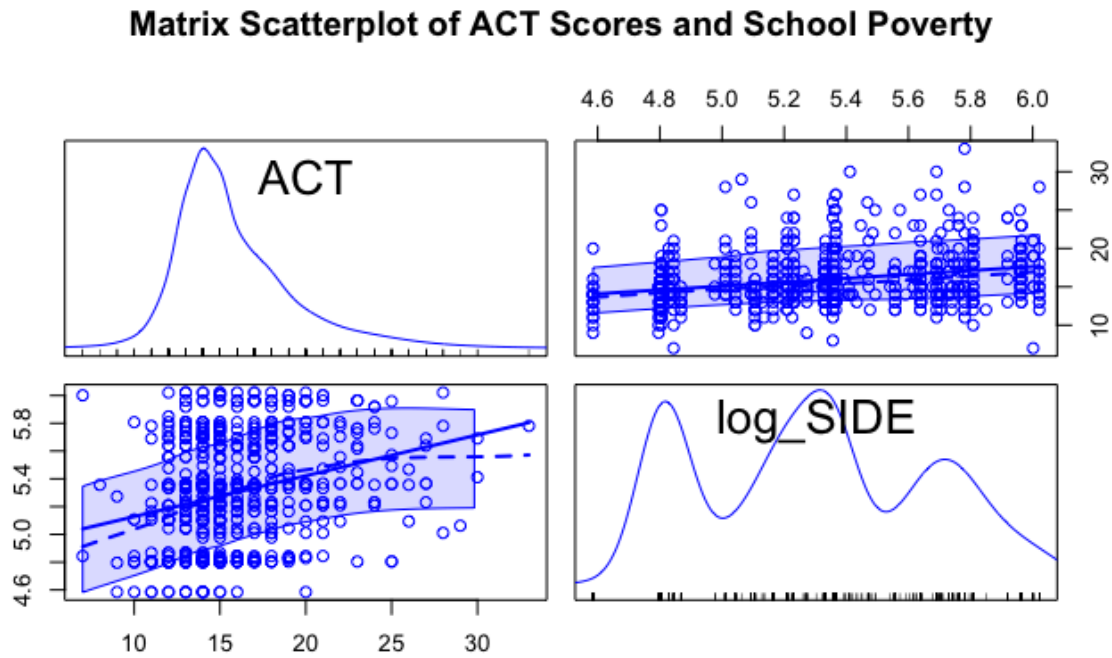


Figure 25.  
Boxplot of Within-Group Sample SIDE IPR Values by End Status

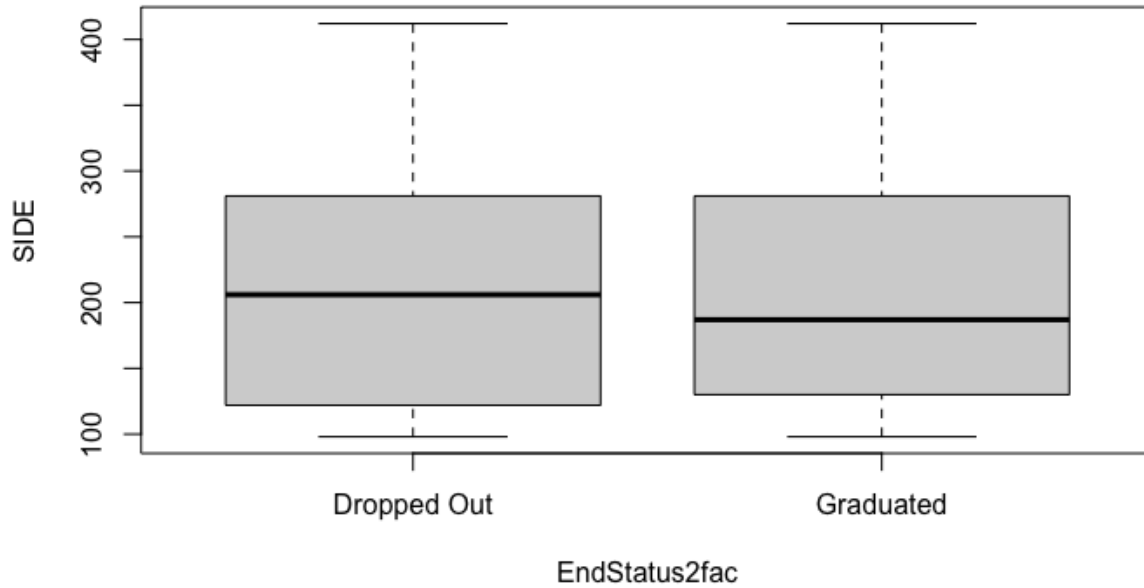


Figure 26.  
Boxplot of Within-Group Sample ACT Scores by End Status

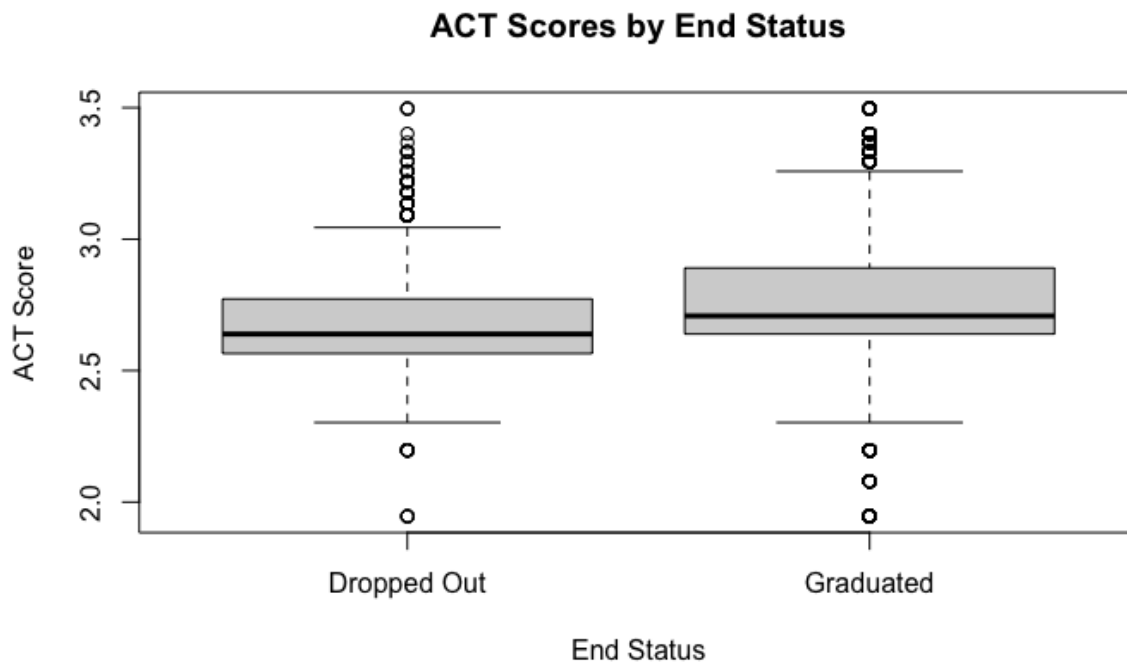


Figure 27.

Mosaic Chart of Student Mobility by Academic Completion for the Within-group Sample

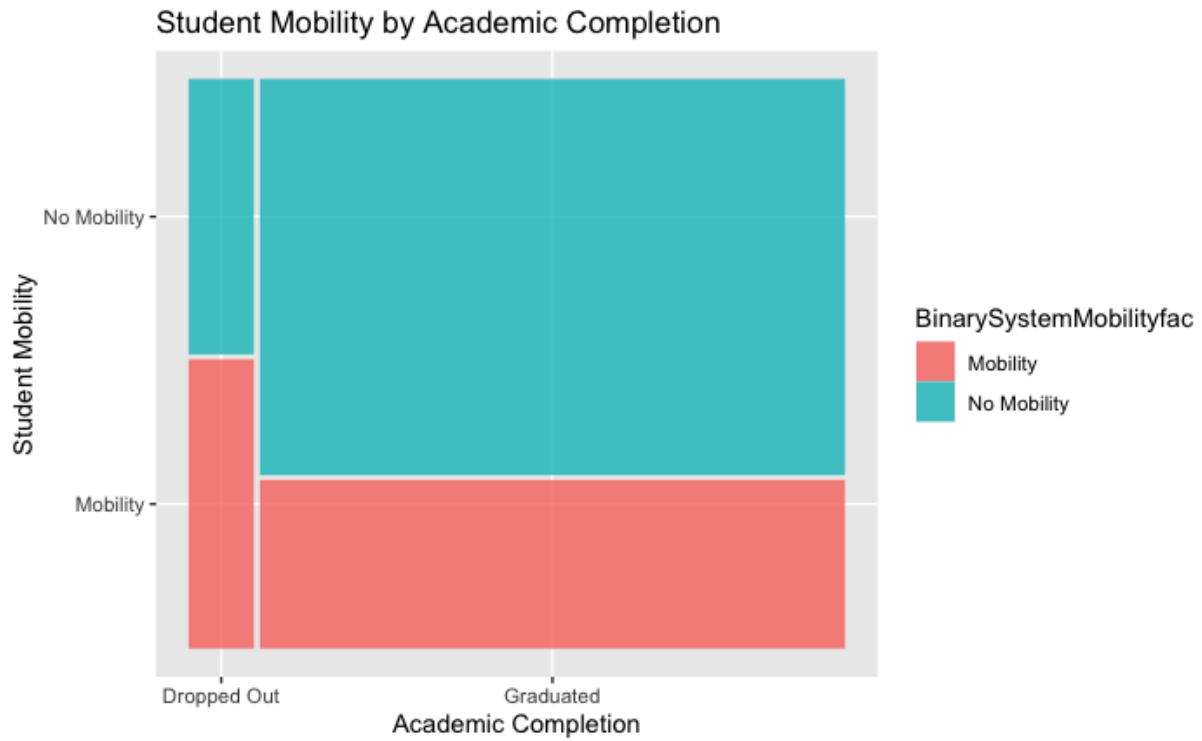


Figure 28.

Boxplot of ACT Scores by Student-Level Poverty for the Within-group Sample

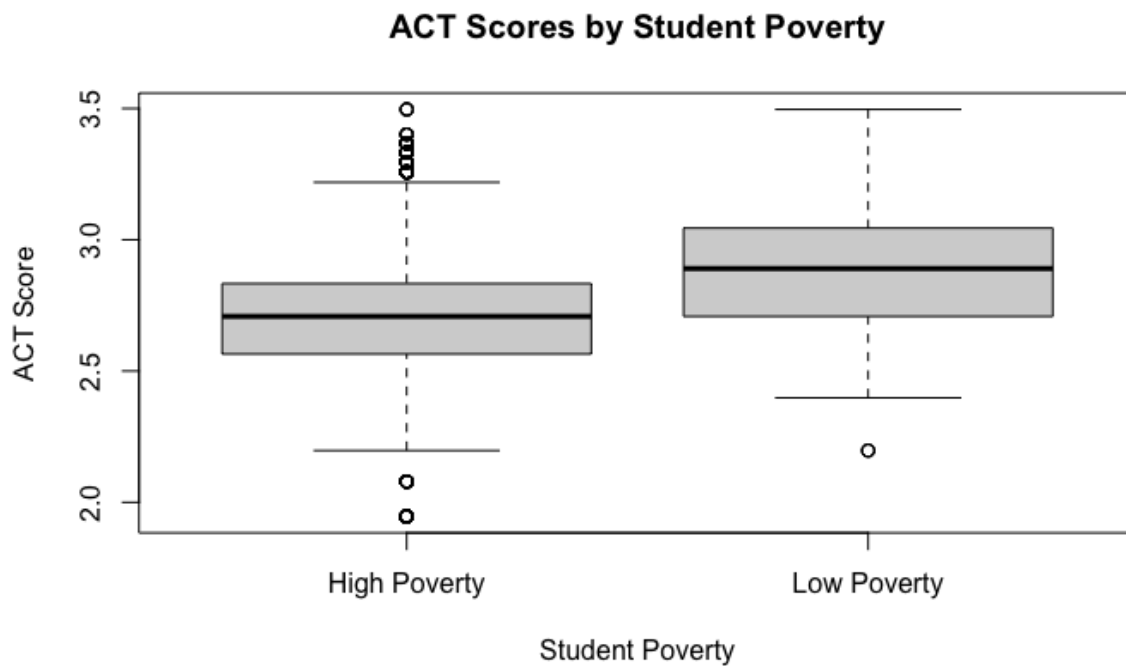


Figure 29.  
Boxplot of School-level Poverty by Student-Level Poverty for the Within-group Sample

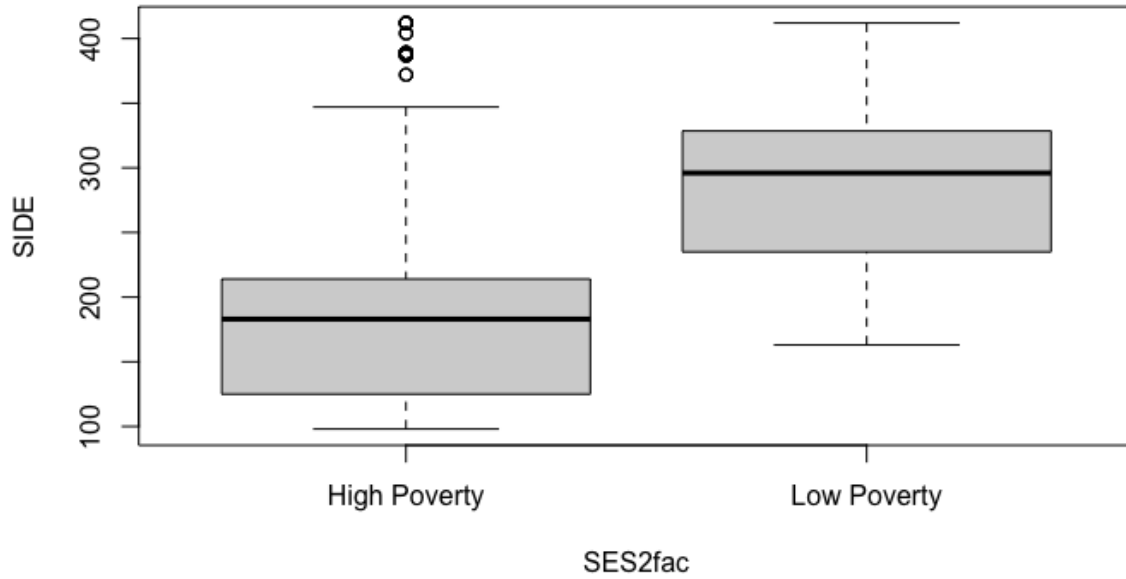


Figure 30.  
Within-Group Sample School Poverty Density Plots Before and After Log Transformation

**ity of Original School Poverty IPR Valuf Log Transformed School Poverty IPR**

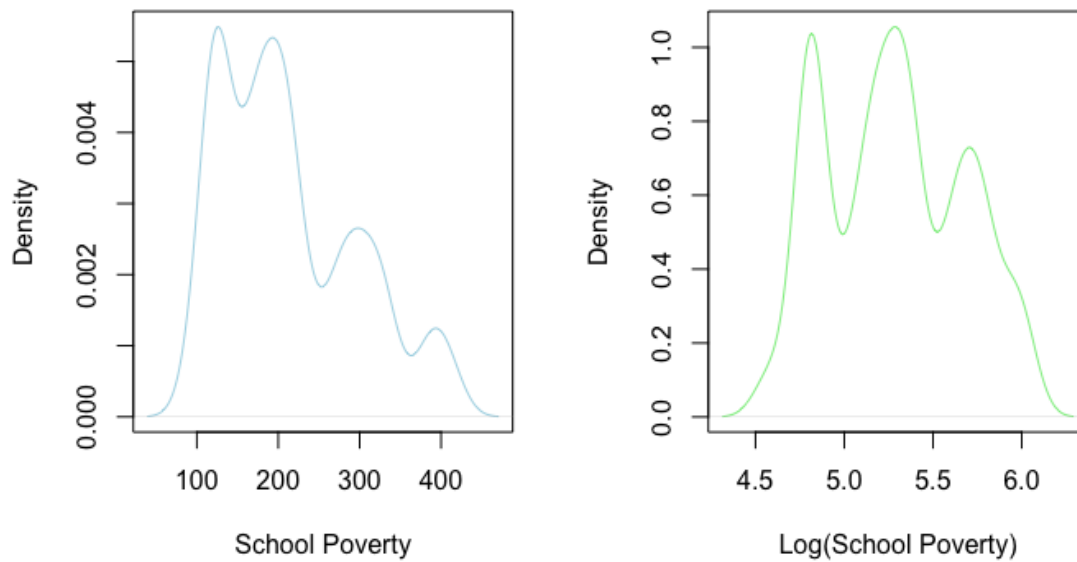


Figure 31.  
 Within-Group Sample School Poverty QQ Plots Before and After Log Transformation

Plot of Original School Poverty IPR Valif Log-Transformed School Poverty IPF

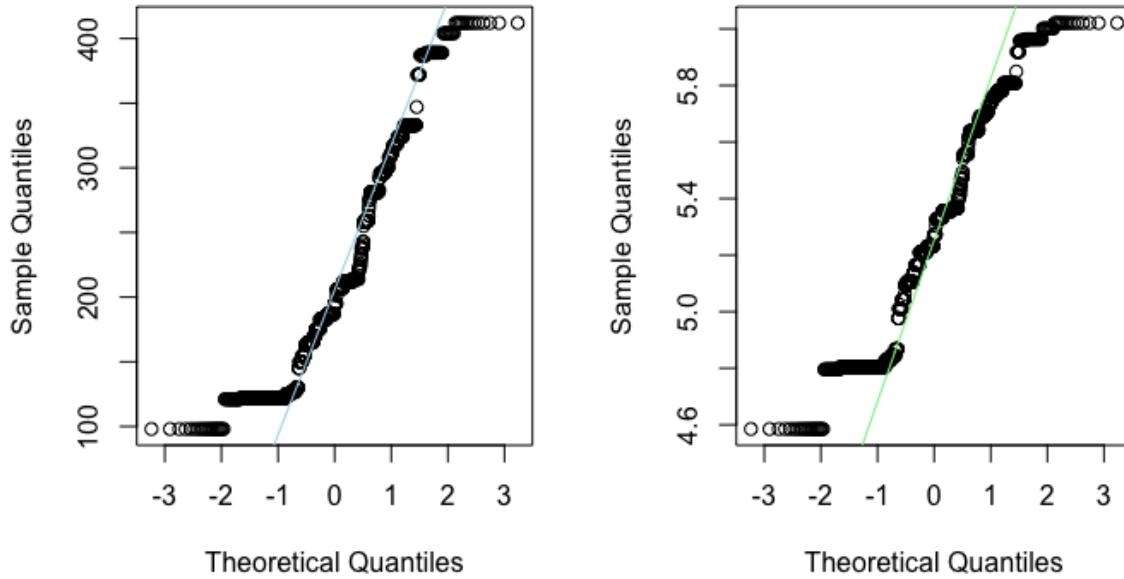


Figure 32.  
 Correlation between School Poverty and ACT Score Coded by End Status

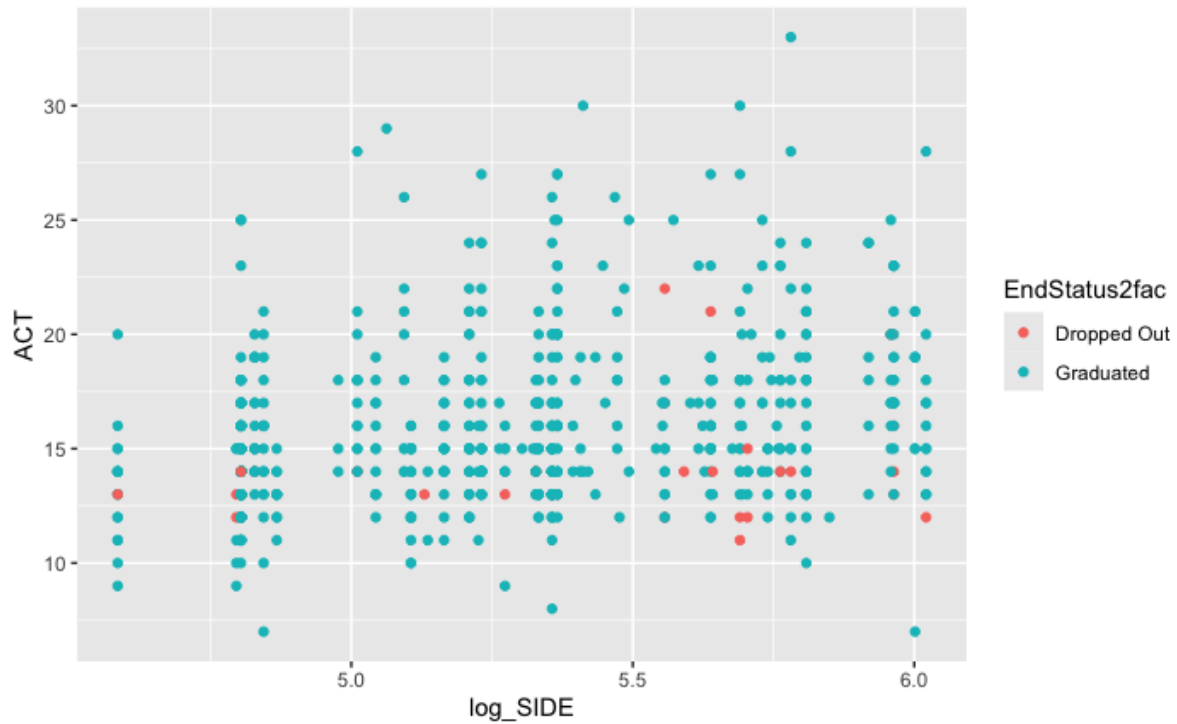


Figure 33.  
Mosaic Chart of Mobility by Reservation Status

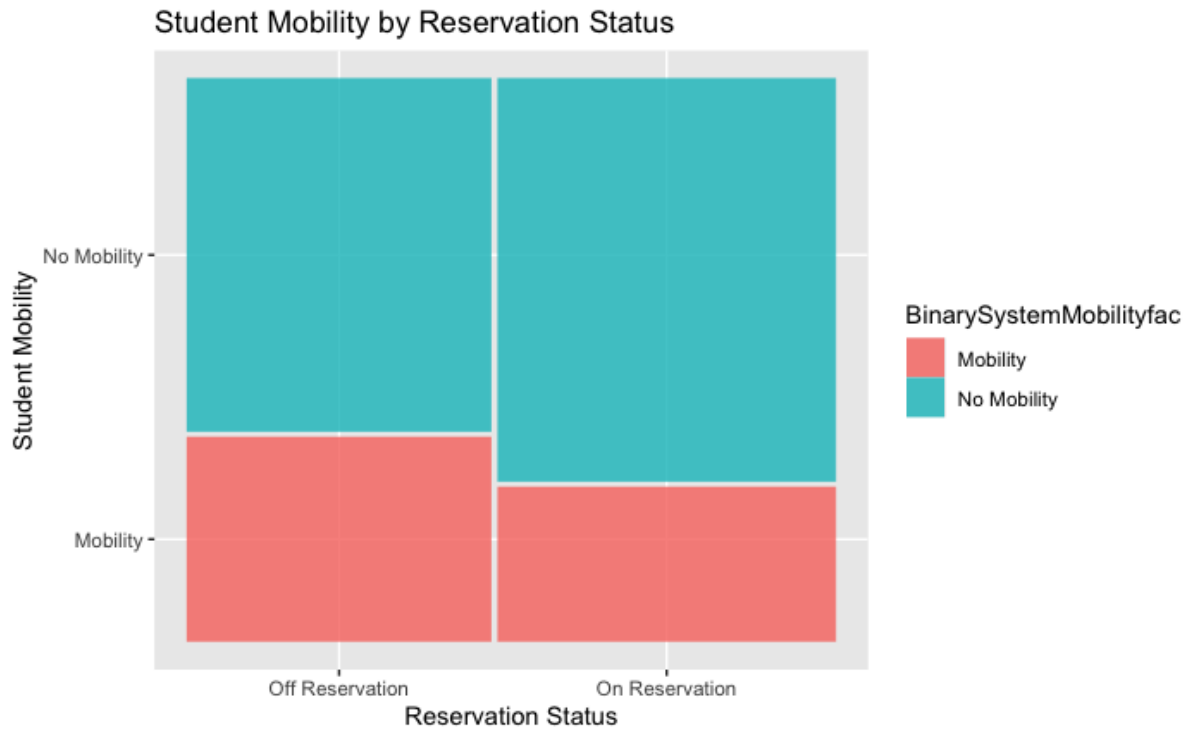


Figure 34.  
Boxplot of Within-Group Sample ACT Score and Binary Mobility

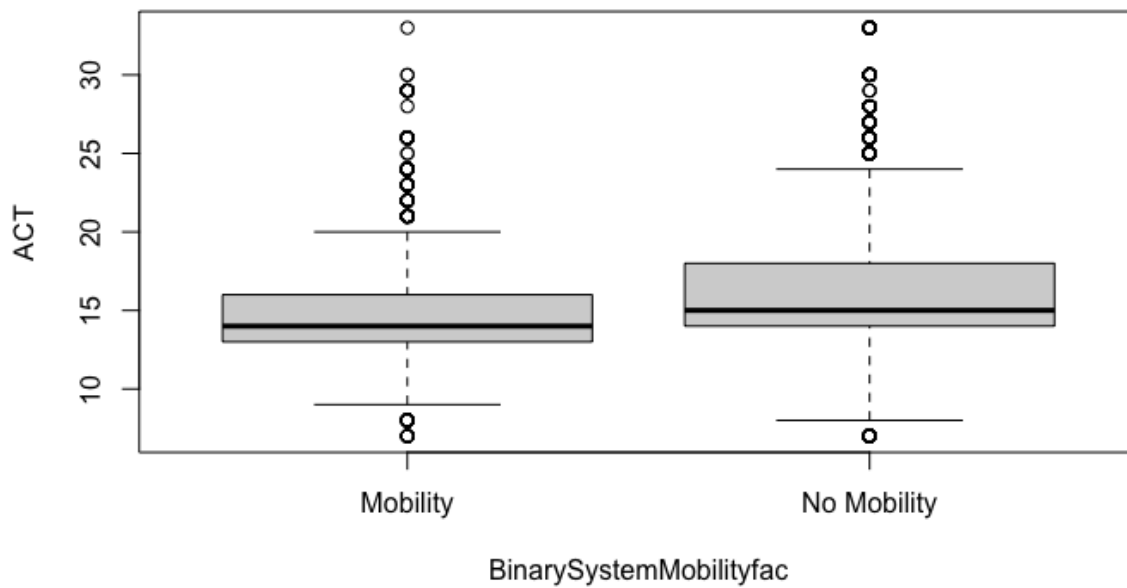


Figure 35.  
Boxplot of Within-Group Sample School Poverty and Binary Mobility

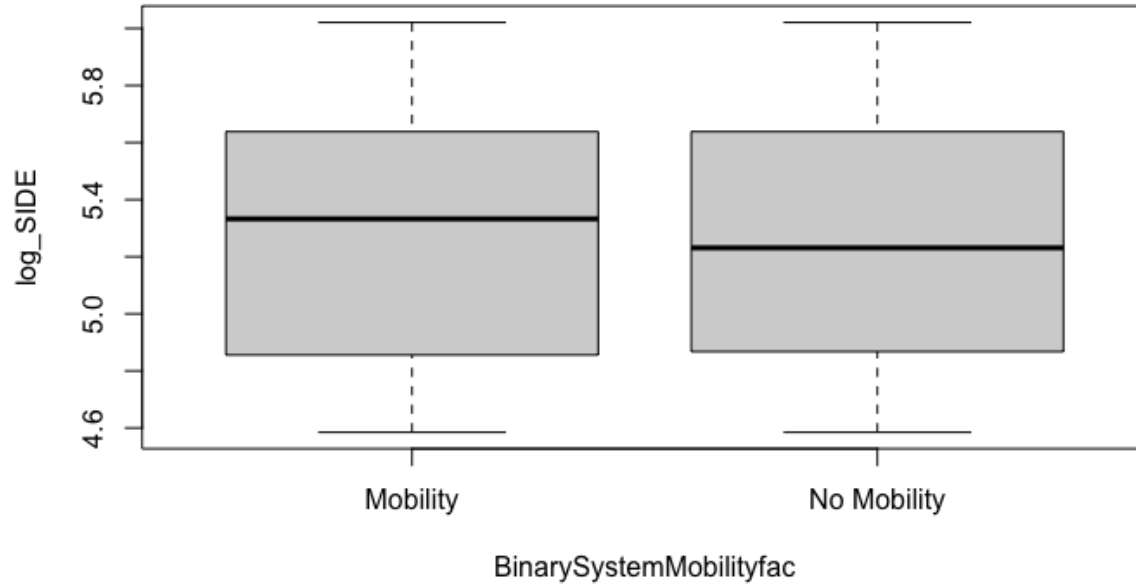


Figure 36.  
QQ Plot of level-1 Residuals for Robust Linear MLM

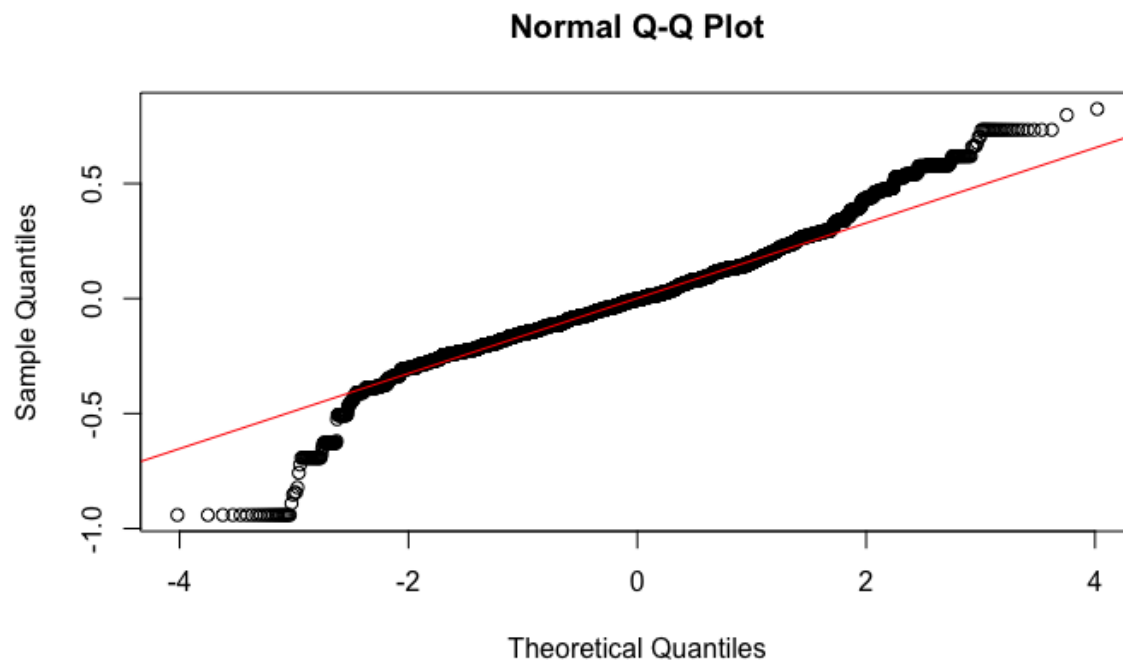


Figure 37.  
Histogram of level-1 Residuals for Robust Linear MLM

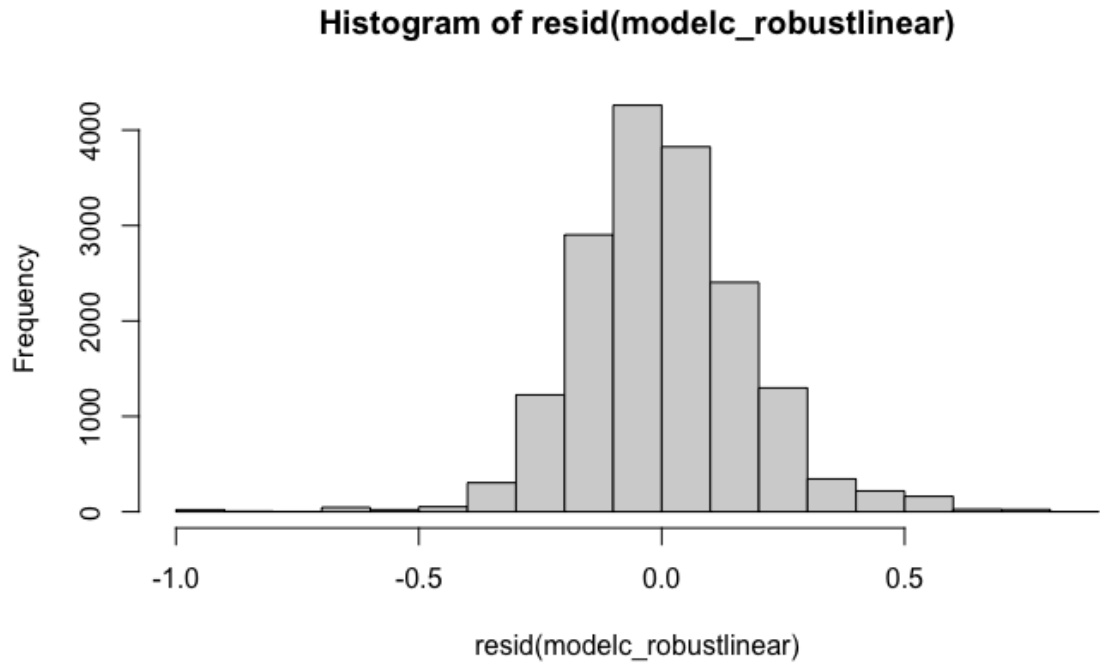


Figure 38.  
Plot of School-level Random Intercepts for Robust Linear MLM

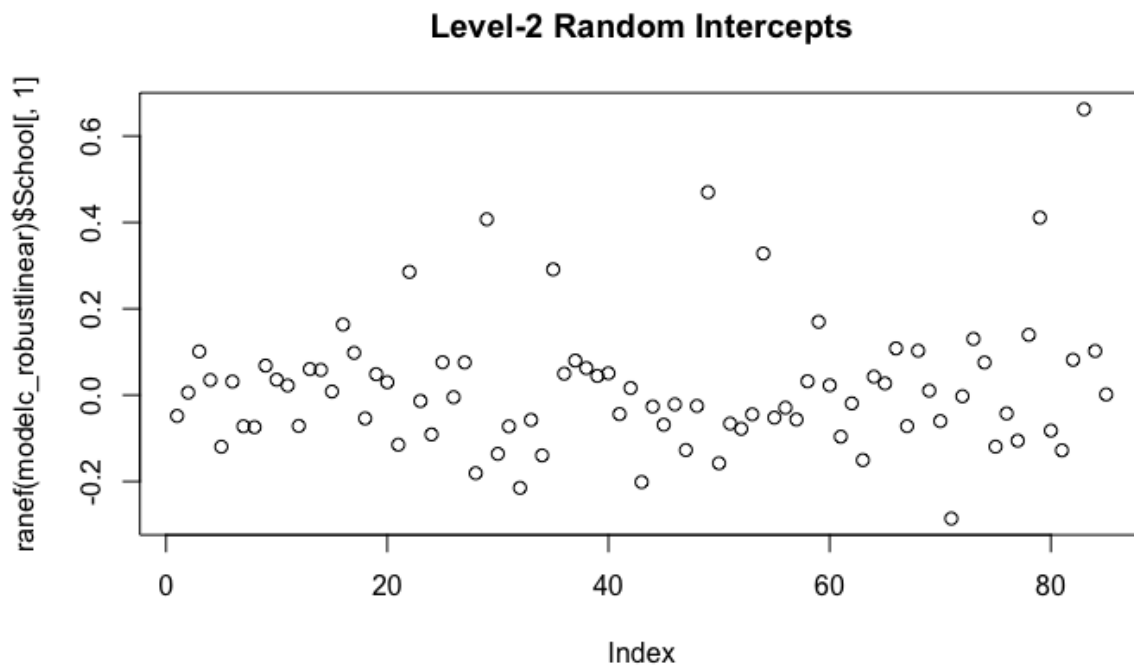


Figure 39.  
Plot of Residuals vs. Fitted Values for Robust Linear MLM

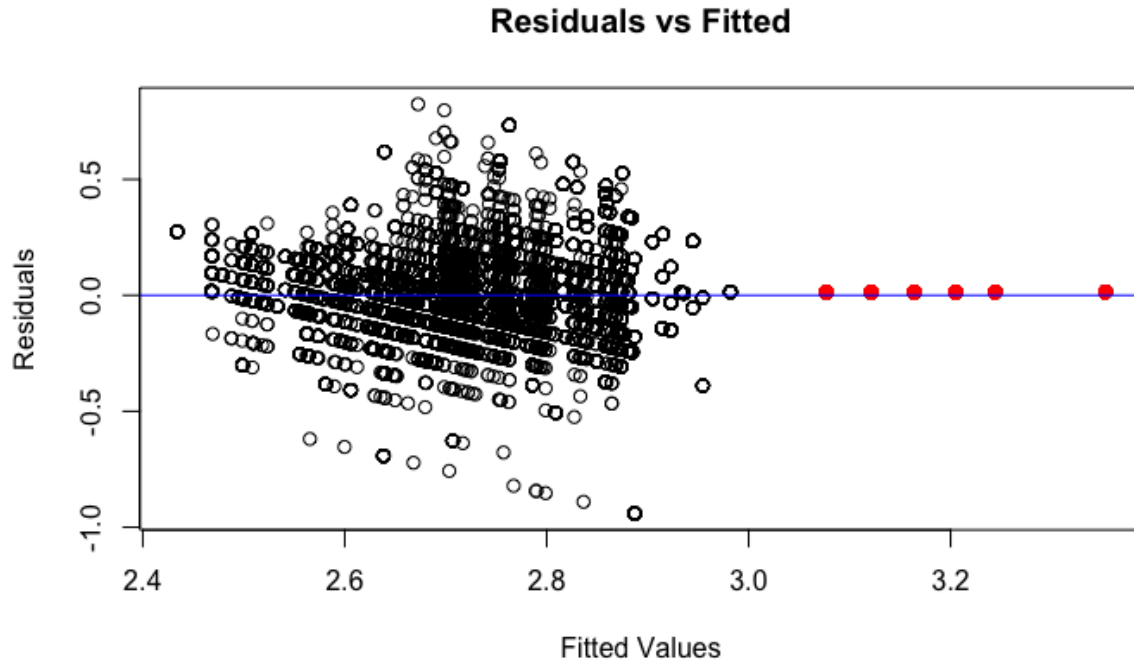


Figure 40.  
Scatterplot of Extreme Observations using Mahalanobis Distance

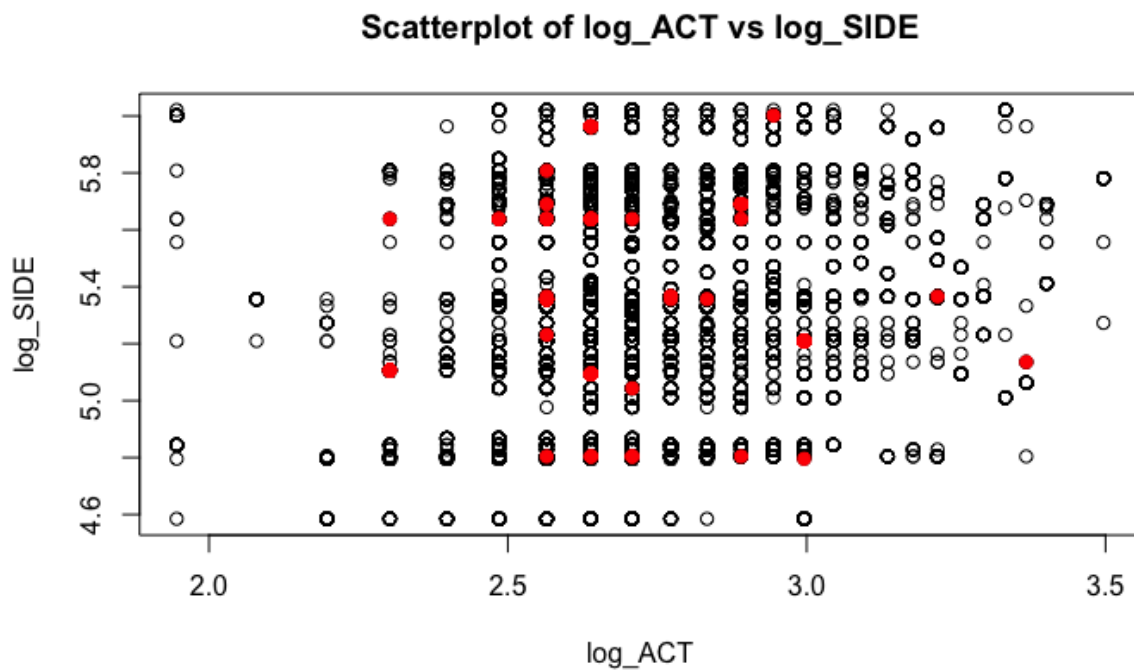


Figure 41.  
Summary of Diagnostic Testing for Robust Linear MLM

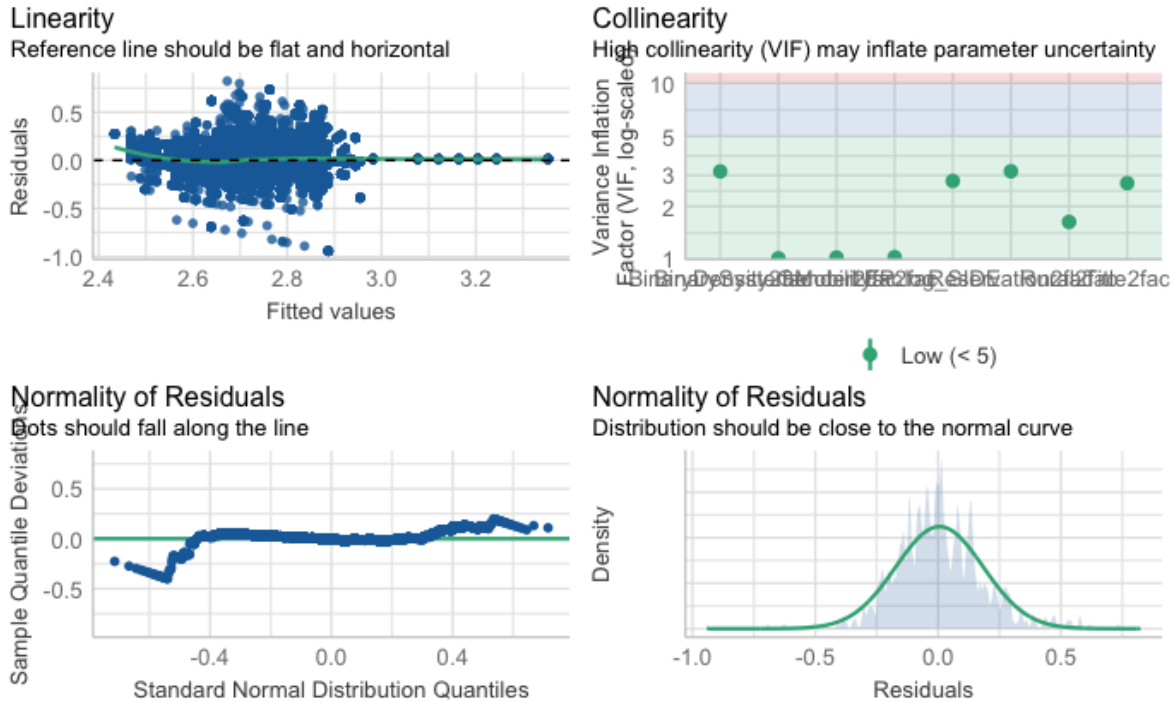


Figure 42.  
ROC Curve for Robust Logistic MLM

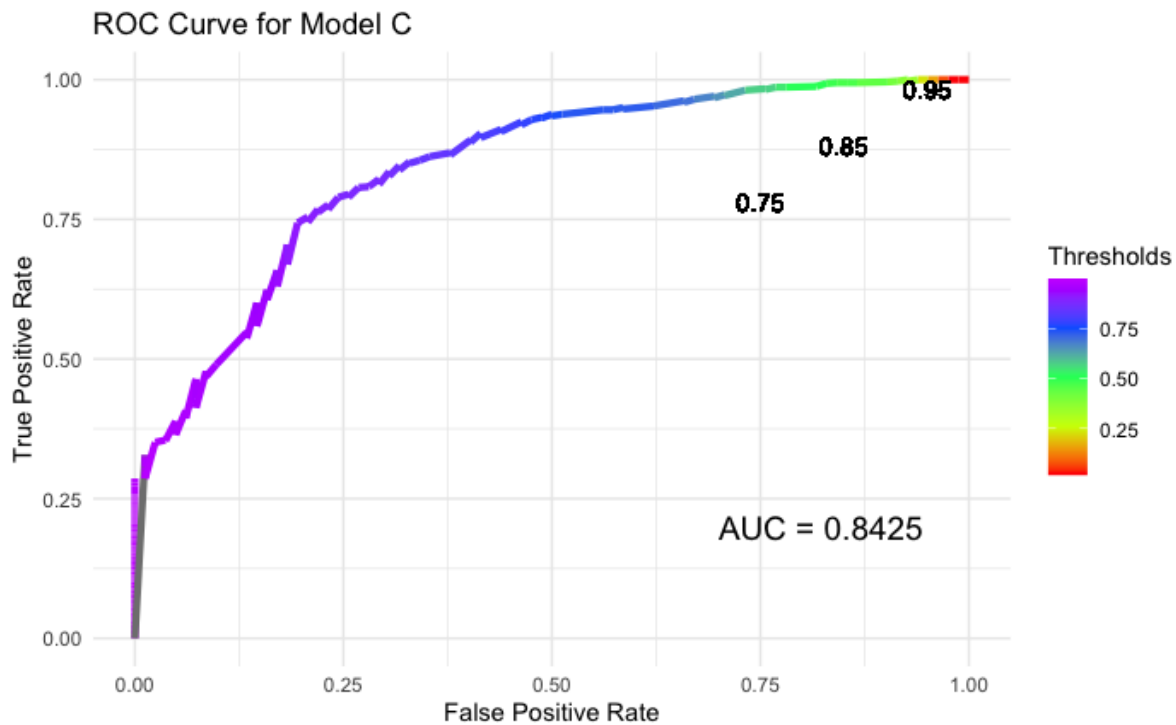


Figure 43.  
Plot of Binned Residuals for Robust Logistic MLM

