A Statistical Examination of Factors Influencing Graduation Status of Students with Disabilities

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MISSY RODDENBERRY

Ed.S., Lincoln Memorial University, 2013
M.A.T., University of Phoenix, 2010
B.B.A., Georgia Southern University, 2001

This dissertation, "A Statistical Examination of Factors Influencing Graduation Status of Students with Disabilities," by Missy Roddenberry, is approved by:

Dissertation Committee Chair & Research Member

E-Ling Hsiao

E-Ling Hsiao, Ph.D.
Professor of Leadership, Technology, & Workforce Development

Committee Members

Signed by:
Marsha Simon
ABAE513BCF1F4BD...

Marsha Simon, Ph.D.
Assistant Professor of Leadership, Technology, & Workforce Development

DocuSigned by:
Matthew Smith
415914B187424E4...

Matthew J. Smith, Ph.D.
Lecturer of Leadership, Technology, & Workforce Development

Associate Provost for Graduate Studies and Research

Becky K. da Cruz

Becky K. da Cruz, Ph.D., J.D.
Professor of Criminal Justice

Defense Date

11/19/2025

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ABSTRACT

The current study examined student-level and school-level factors influencing on-time high school graduation among 425 students with disabilities (SWD) across the 2022, 2023, and 2024 graduation cohorts in a South Georgia school district and compared the predictive accuracy of multiple statistical and machine learning models. Results revealed that students who were not chronically absent and those spending more time in general education classrooms had substantially higher odds of graduating. In contrast, students placed in alternative schools demonstrated lower graduation odds. Unexpectedly, students who qualified for free or reduced-price lunch had higher graduation odds in this district, contradicting national patterns linking economic disadvantage to lower graduation rates. In addition, logistic regression provided the highest overall accuracy (82.4%) and interpretability, compared to neural network, random forest, and support vector machine models. For class imbalance, none of the models accurately classified non-graduates, with specificity ranging from 29% to 48%. These results highlight the importance of early detection and intervention efforts focused on attendance, inclusive placement, and support for students in alternative settings. While advanced machine learning models offer incremental gains in accuracy in some contexts, the current study highlights the practical value of logistic regression for school districts seeking clear, data-driven methods to identify students at risk and inform policy interventions that support the graduation of students with disabilities.

TABLE OF CONTENTS

LIST OF TABLES

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Chapter I

Introduction to the Study

Educational leaders recognize high school graduation as a critical step toward the future success of students and local economies (Harmon & Smink, 2017). Graduation is the ultimate goal educators strive for, representing the culmination of their students' educational journey and celebrating their dedication and perseverance in the pursuit of knowledge. Unfortunately, not all students can achieve this goal. To be considered a graduate in the state of Georgia, students must attain a Regular Diploma, which satisfies attendance, unit, and state assessment requirements (GaDOE, 2021), not a Certificate of Attendance or Special Education Diploma. An individual enrolled in grades 9 through 12 during the current or previous school year but no longer enrolled is considered a dropout (Kaufman et al., 2000). Students who leave school with a Certificate of Attendance or Special Education Diploma, in addition to one of the following 11 reasons, are considered dropouts: marriage, expulsion, financial hardship, incarceration, failure, military service, adult education, pregnancy, lack of attendance, serious illness, or unknown reasons (GOSA, 2020). While these dropout reasons are indicative of why a student may drop out, a “youngster’s leaving school before graduation may be just one more event, albeit a conspicuous event, in a chain that may have begun years before” (Finn, 1989, p. 118).

Every year, several million students nationwide drop out of high school and integrate into the community (NCES, 2021a). The repercussions of high school dropout extend beyond the educational sphere, casting a detrimental shadow over society due to the many negative consequences of not obtaining a high school diploma. One such adverse consequence is the diminished employability of high school dropouts (Andersen et al., 2021; Christle et al., 2007; Kortering & Braziel, 2002). In August of 2024, the unemployment rate for individuals who left high school prematurely was 7.1%, compared to 4.0% for those who successfully completed high school (U.S. Bureau of Labor Statistics, 2024). High school dropouts are more likely to have lower incomes, as corroborated by a press release issued by the U.S. Bureau of Labor Statistics (2023). This source revealed that the median weekly earnings of full-time workers without a high school diploma were $726. In contrast, their counterparts with a high school diploma earned a median weekly income of $916, and those with a bachelor's degree earned $1,684.

In addition to the elevated risk of unemployment and diminished income prospects, high school dropouts face a spectrum of negative consequences. They are more likely to engage in criminal activities, including gang-related activity and drug abuse (Christle et al., 2007; Prevatt & Kelly, 2003), experience a heightened likelihood of health issues (Prevatt & Kelly, 2003), and exhibit higher rates of unplanned parenthood (Kortering & Braziel, 2002). Moreover, these individuals are susceptible to adverse outcomes, such as an increased risk of incarceration, substance abuse, and reduced adult productivity (Bear et al., 2006). The ramifications of the decision to abandon high school extend far beyond the individual and adversely impact society. Many dropouts rely on welfare systems for support (Garnier et al., 1997) or become entangled in the criminal justice system (Dunn et al., 2004), both of which strain the economy. Given the multitude of detrimental effects on society and the economy, it is evident that high school dropout rates constitute a significant national concern (Christle et al., 2007).

The issue of students dropping out of high school has been the subject of research and documentation for many decades. As early as 1927, this phenomenon was referred to as “school leaving.” Scholars have addressed this issue ever since (Doll et al., 2013). Over the past four decades, research on dropouts has undergone a notable shift in focus. During the 1980s, research studies primarily concentrated on student-level factors that might contribute to a student’s decision to drop out. These factors included academic achievement, attendance, cognitive ability, grade retention, and substance use (Garnier et al., 1997). In the subsequent decade, research expanded its purview to consider dropping out as a result of a combination of individual, family, and school experiences (Garnier et al., 1997). This broader perspective sought to uncover the complex interplay of factors that contribute to students leaving high school before graduation, thereby negatively impacting graduation rates.

President George H.W. Bush catalyzed a nationwide focus on graduation rates, setting the goal of achieving a 90% graduation rate by 2000. In 1990, the Office of Special Educational Programs (OSEP) established initial requirements for reporting dropout rates among students with disabilities (Kemp, 2006). Following these initial efforts to address the graduation rate, subsequent legislations were enacted to foster accountability in this domain.

A pivotal moment occurred with the implementation of the federal No Child Left Behind Act (NCLB) in 2001, which significantly influenced the examination of high school dropout rates. This legislative mandate introduced accountability measures to ensure high school completion for all students, including students in various subgroups (Reschly & Christenson, 2006). Notably, incorporating subgroups, including students with disabilities, within NCLB's accountability framework, marked a transformative shift in the approach adopted by educational institutions and policymakers towards assessing student graduation rates (McLaughlin & Thurlow, 2003).

Although extensive research has been conducted on the subject of high school dropouts, the majority of studies have not directed their focus toward students with disabilities. These studies often incorporate students with disabilities as a subgroup within their analysis, without conducting separate analyses (Blazer & Gonzalez Hernandez, 2018; Finn, 1989; Rumberger & Lim, 2008; Shannon & Bylsma, 2006). This research gap is of particular concern due to the potential disparities in dropout rates for students with mild disabilities, which data suggest could be nearly double that of students without disabilities (Dunn et al., 2004). Students with disabilities face challenges that can significantly influence their educational trajectories. Despite these challenges, this population has typically been marginalized in research. While more recent studies have begun to incorporate students with disabilities into their research, this population has been historically underrepresented in the literature (Reschly & Christenson, 2006).

Among students who dropped out within the past 14 years, the percentage of students with disabilities who did not attain high school graduation has consistently hovered approximately 20% higher than that of their non-disabled peers (New England Secondary School Consortium, 2022). Notably, the dropout rates for students with disabilities have exhibited a downward trend over the last decade. Specifically, these rates decreased from 21.1% in 2010 to 16.6% in 2019 (U.S. Department of Education, 2021). However, despite this improvement, the dropout rates among students with disabilities remain considerably elevated compared to the broader student population. In 2010, the overall dropout rate was reported to be 7.4%; by 2020, it had decreased further to 5.3% (NCES, 2022). Despite the observed decreases in dropout rates, students with disabilities still exhibit a high school dropout rate that surpasses the overall dropout rate by over three times (NCES, 2022; U.S. Department of Education, 2021).

Statement of the Problem

To reduce the number of students dropping out of high school and enhance societal well-being, targeted efforts are crucial, especially for vulnerable subgroups like students with disabilities. According to the National Center of Education Statistics (2022) and the U.S. Department of Education (2021), students with disabilities have significantly higher dropout rates compared to their peers without disabilities. In 2021, the dropout rate for students without disabilities was 4.8%, whereas for students with disabilities, it was substantially higher at 10.4% (NCES, 2022). The persistent elevation of dropout rates among students with disabilities underscores the urgent need for interventions. As enrollment of students with disabilities continues to rise, from 6.4 million during the 2010-2011 school year to 7.3 million in the 2021-2022 school year, it becomes paramount to equip educators with the necessary tools for promoting continuing education and graduation (NCES, 2023c)

While the decision to discontinue formal education is individual, researchers have identified predictive factors, including poor academic performance and behavioral concerns (Bear et al., 2006). Student engagement and grade retention also significantly predict dropouts (Alexander et al., 2001). Although student-level attributes have been explored, such as disability classification, English proficiency, gender, race and ethnicity, and socioeconomic status (Christle et al., 2007; McDermott et al., 2019; Rumberger & Lim, 2008; Zablocki & Krezmien, 2013), these studies mainly focused on the general education student population. Further research is essential to address dropout rates among students with disabilities and to understand disparities in academic outcomes compared to their peers in general education (NCES, 2022), providing insight into targeted reduction efforts within this specific demographic.

Purpose of the Study

The purpose of the current study was to analyze data from three cohorts in a South Georgia school district, providing teachers and administrators with insights into potential factors influencing students with disabilities' decisions to drop out of school, thereby affecting their graduation status. By identifying these factors, the current study aimed to explore potential strategies for improving graduation rates among this subgroup of students. While numerous factors have been linked to students' decisions to remain enrolled or drop out of school, Dynarski et al. (2008) emphasized the importance of examining both student-level and school-level influences. Therefore, the current study concentrated on student-level and school-level factors. Student-level factors included demographic characteristics such as disability classification, English proficiency, gender, race and ethnicity, and socioeconomic status, as well as academic factors like the number of failed classes and grade retention, and the non-academic factors such as student attendance and behavior challenges (Dunn et al., 2004; Hammond et al., 2007; Kart & Kart, 2021; Kurth et al., 2019; Schwartz et al., 2019). School-level factors focused on services provided through students' Individualized Education Programs and the learning environments (Hammond et al., 2007; McDermott et al., 2019; Ramsdal & Wynn, 2022; Wagner et al., 2006; Zablocki & Krezmien, 2013).

Research Questions

The research questions framing the current study were:

1. Are any student-level or school-level factors significant predictors of high school graduation status for students with disabilities?

2. Which of the data mining models (binomial logistic regression, neural network, random forest, and support vector machine) can generate a more accurate prediction of high school graduation status based on the evaluation metrics of accuracy, precision, recall, and F1 score?

Research Methodology

The research design for the current study was a non-experimental, correlational research, focusing on the dependent variable—graduation status—of students with disabilities, using independent variables related to student-level and school-level factors. A correlational methodology was appropriate for the current study because statistical analysis was needed to identify significant factors associated with high school students' likelihood of dropping out or graduating (Creswell & Creswell, 2018). Data were compiled from historical records from a mid-sized rural school district in South Georgia. This school district was selected due to the researcher's professional affiliation with the site and the potential for the data to inform positive changes within the district. This selection enabled an in-depth analysis of the relationships between student-level and school-level factors and high school graduation status among students with disabilities.

The historical data encompassed all students from the graduation cohorts of 2022, 2023, and 2024, covering all high schools within the district. The subset of interest for analysis consisted of students identified with a disability category who received special education services. According to a report compiled by the district's Information Systems Department (personal communication, September 5, 2024), the estimated sample size for students with disabilities within the graduation cohorts was 673. This estimate was based on graduation cohort data, including 240 students with disabilities from the 2018–2022 cohort, 250 from the 2019–2023 cohort, and 183 from the 2020–2024 cohort.

Data collection for the current study drew from various sources, predominantly within the Georgia Department of Education (GaDOE). Annually, school districts report information to the GaDOE through multiple data collection processes. The GaDOE computes and provides data files containing calculated values derived from these collections. This compilation process produces extracts that include student demographic information (e.g., disability classification, English proficiency, gender, race and ethnicity, and socioeconomic status), as well as academic (e.g., failed classes and grade retention) and non-academic performance data (e.g., attendance and behavior referral data), and school-level data including Individualized Education Plan (IEP) services (e.g., collaborative instruction, consultative service, co-teaching instruction, direct instruction, and supportive services) and learning environments (e.g., alternative school, general and special education classrooms, and separate special education school). Primary data sources included the June-reported Student Record and Student Class data collections and the fall-reported College and Career Performance Readiness Index (CCRPI), both sourced from the GaDOE (n.d.-b) and Georgia Insights (n.d.). The district's Information Systems Department housed and managed the data, and served as the point of access.

The school district in the current study utilized Infinite Campus as its student information system (SIS). Infinite Campus is used by approximately 2,400 school districts across 46 states (Infinite Campus, n.d.) and represents 68.1% of SIS usage among Georgia school districts (GSIS Users Organization, n.d.). Other SIS platforms used in Georgia include PowerSchool, Aspen, and Synergy (EduPoint, n.d.; GSIS Users Organization, n.d.; K. Sinha, personal communication, May 18, 2024). Data obtained from Infinite Campus was cross-referenced with information from the data collection files when necessary. Infinite Campus stores a wide range of student data, including demographics, academic performance (e.g., failed classes and grade retention), and non-academic performance (e.g., attendance and behavior referral data). The Information Systems department managed access to the Infinite Campus database, which generated the necessary reports for information retrieval. To comply with the Family Educational Rights and Privacy Act (FERPA) (U.S. Department of Education, n.d.), all student services and placements were extracted using unique identifiers for cross-referencing. Any data containing Personally Identifiable Information (PII) were randomized prior to analysis to protect student privacy (Protecting Student Privacy, n.d.).

Several statistical analyses were employed in this quantitative research study to address the research questions. Binomial logistic regression was used to assess the relationship between student-level and school-level factors and the binary graduation status—either graduation or dropout—for the first research question. The second research question was addressed by applying binomial logistic regression, neural network, random forest, and support vector machine to determine which method provided the most accurate predictions. The models were compared using evaluation metrics of accuracy, precision, recall, and F1 score. This comparison identified the most effective predictive model for understanding graduation outcomes among students with disabilities.

Conceptual Framework

Numerous theories have been used to investigate factors influencing students' decisions to leave school prematurely. Although the current study does not employ these theoretical frameworks, it is important to recognize their significance in previous research. One such framework, introduced by Gary Wehlage and colleagues, focuses on school membership and educational engagement (Rumberger & Lim, 2008) and offers valuable insights into factors contributing to student dropout rates. Similarly, Jeremy Finn's model applies the "frustration-self-esteem" and "participation-identification" frameworks to explain the underlying causes of dropout (Rumberger & Lim, 2008). Although not directly applied in the current study, these theories have significantly contributed to a broader understanding of dropout dynamics.

In the context of the current study, the theoretical foundation for exploring the interaction of various factors and variables draws from the work of Hammond et al. (2007). Hammond and colleagues conducted comprehensive research, analyzing 44 studies spanning from 1974 to 2002, aiming to identify risk factors contributing to students' likelihood of dropping out of school. Their research categorized these factors into four domains: the Individual Domain, the Family Domain, the School Domain, and the Community Domain. The Individual Domain includes factors such as students' background characteristics, early adult responsibilities, social attitudes and behavior, and school performance, engagement, and behavior. The Family Domain encompassed family background characteristics, household stress levels, family dynamics, and educational commitment. The School Domain comprised factors related to school structure, resources, student body characteristics and performance, school environments, academic policies, discipline policies, and practices. The Community Domain included location, type, demographic characteristics, and environments (Hammond et al., 2007).

According to Dynarski et al. (2008), preventing dropout for at-risk students should begin with identifying student-level and school-level problems before implementing interventions. For the current study, only the Individual Domain, including one factor from the Family Domain, and a portion of the School Domain from Hammond's research were utilized. These domains included variables available to school districts through annual reports from the Georgia Department of Education, ensuring that the historical data are accessible and consistently reported for analysis. Family and community factors were excluded from the current study due to challenges in obtaining reliable data on them, including privacy concerns and variability across data sources.

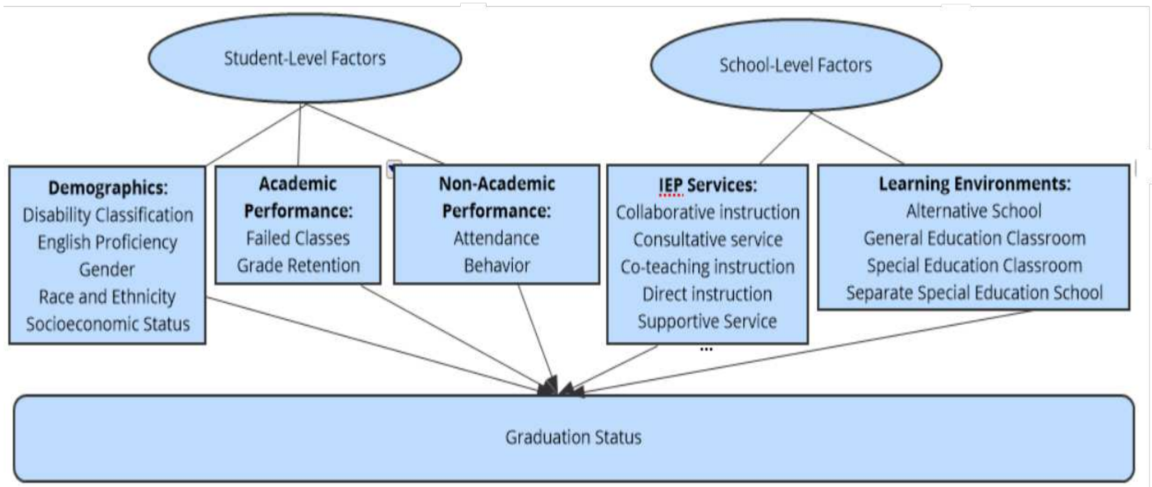
The Individual Domain highlighted high-risk demographic characteristics, including disability classification, English proficiency, gender, and race and ethnicity (Hammond et al., 2007). While socioeconomic status is traditionally classified under the Family Domain, as shown in Figure 1, the current study treated it as an individual student characteristic for analytical purposes. Additionally, this domain encompassed various other factors, such as poor school performance and different forms of disengagement—academic, behavioral, psychological, and social (Hammond et al., 2007). Poor school performance was assessed through academic factors, including failed classes and grade retention. To assess disengagement, the current study adopted the model proposed by Newman (1992), utilizing non-academic factors such as attendance and behavior referrals as observable indicators, acknowledging that engagement itself is not readily observable (Rumberger & Lim, 2008).

Factors in the Individual Domain that were not included in the current study included immigration status, early adult responsibilities, high-risk attitudes, and educational stability. Furthermore, other individual factors, such as involvement with drugs and alcohol, family instability, uninvolved parents (Harmon & Smink, 2017), negative interactions with peers or school personnel, and participation in extracurricular activities (Kemp, 2006), were considered in other research but were not part of Hammond's theory or the current study.

The first research question in the current study examined the predictive value of student-level factors, including high-risk demographic characteristics, academic performance, and non-academic performance, as identified in the Individual Domain by Hammond et al. (2007), in relation to graduation status among students with disabilities. Additionally, this research question adapted the School Domain, which consisted of school structure, resources, student body characteristics and performance, school environments, academic policies and practices, and supervision and discipline policies (Hammond et al., 2007), by focusing on learning environments (alternative school, general and special education classrooms, and separate special education school) and academic practices, specifically IEP services (collaborative instruction, consultative service, co-teaching instruction,, direct instruction, and supportive service) provided to students as school-level factors.

Figure 1

Concept Map for Factors Affecting Student Graduation Status



Significance of the Study

The current study holds significance for several reasons. First, it targeted the population of students with disabilities. While numerous studies have focused on dropout rates within the general education population, there is a notable scarcity of research explicitly examining dropout rates among students with disabilities in this context (Reschly & Christenson, 2006). The current study focused on a group of students with disabilities, examining the impact of student-level and school-level factors on this specific demographic. By identifying these factors that may contribute to students with disabilities dropping out of school, we can proactively identify at-risk students and implement interventions to reduce their likelihood of discontinuing their education.

Second, existing literature exploring the connection between students with disabilities and dropout rates lacks a detailed examination of individual disability categories and their potential impact on dropout likelihood. Instead of treating students with disabilities as a homogeneous group, the current study categorized this population into distinct disability groups to determine how various factors affect students within each disability category. This granular understanding of the relationship between factors and specific disabilities could serve as a valuable tool for identifying and supporting at-risk students. Finally, the adverse consequences of students prematurely leaving the educational system are well documented. Ongoing research is crucial for equipping educators and administrators with insights into the factors that influence students' decisions to drop out and impact their graduation status. These insights can drive changes in learning environments and services provided to students with disabilities, potentially leading to improved grade retention rates throughout their academic journey, including until graduation. Increasing the graduation rates of students with disabilities, which consistently fall below those of their general education peers (NCES, 2022), is a potential outcome of the knowledge derived from the current study.

Assumptions, Limitations, and Delimitations of the Study

Assumptions

This current study was conducted under several key assumptions necessary for analyzing the factors affecting the graduation status of students with disabilities. First, it assumed that the data submitted by the school district to the GaDOE were both accurate and reliable. While human error in data entry was acknowledged as a potential limitation, the study assumed that such errors were random and therefore did not introduce significant bias into the findings. Additionally, it was presumed that the data collection procedures remained consistent across the six-year span from the start of the 2018-2022 cohort to the end of the 2020-2024 cohort. The school district was assumed to have adhered to the GaDOE’s standardized protocols for reporting student information, ensuring comparability over time.

Another key assumption was that the statistical methods employed in this analysis met the necessary conditions for validity, including normality, independence of observations, and homoscedasticity. Several specific assumptions must be met when utilizing a binomial logistic regression model for data analysis. These include a dichotomous dependent variable, one or more independent variables that are categorical or continuous, and a linear relationship between the independent variables and the logit transformation of the dependent variable. Ensuring that these assumptions were satisfied was critical for producing valid results (Laerd Statistics, n.d.). Finally, it was assumed that the historical dataset provided was complete, containing all relevant variables needed to investigate graduation rates of students with disabilities.

Limitations

Several limitations were associated with the current study. First, concerns arose regarding the accuracy of the data. The data extracts, sourced from the GaDOE, were official documents used for graduation rate calculations and constituted the authoritative data for the school district. Nevertheless, the data originated in district submissions to the state from the student information system. The data involved multiple data entry points across the school system, including attendance, behavior referrals, demographics, school withdrawal codes, socioeconomic status, and more. Potential human errors during data entry were acknowledged as a plausible limitation.

Second, the study’s scope was limited to a single school district due to challenges in accessing comparable data from other districts that included the necessary variables without requiring the use of a Georgia Testing Identifier (GTID), which is classified as PII. Consequently, the findings were not universally applicable for comparative analyses across different districts or different states. Another limitation stemmed from the data collected and utilized for the analysis. Sole reliance on historical data for investigating dropout-related factors negated the possibility of including more personalized or comprehensive variables attainable through surveys or interviews with dropouts. I also could not manipulate variables through a true experimental procedure to establish definitive cause-and-effect relationships since the data already existed. Lastly, the study also faced constraints related to the assumptions underlying the statistical analyses, as violations of these assumptions affected the validity of the findings.

Delimitations

The current study was delimited by several factors that defined its scope and focus. First, the research was intentionally limited to one school district within the state of Georgia. This choice enabled a more robust analysis of factors affecting the graduation status of students with disabilities, but limited the generalizability of the findings beyond the specific districts studied. Additionally, the study relied on data provided to and from the GaDOE, specifically Student Class files, Student Record files, and CCRPI reports. The use of these data limited the inclusion of qualitative factors, such as personal experience or outside influences, which would have provided a more individualized context. Additionally, the current study included only the individual domain and a portion of the school-level domain, without considering the family and community domains proposed by Hammond et al. (2007), which may have potentially influenced the graduation outcomes of students with disabilities. However, these factors have been excluded from the study due to concerns about privacy and variability in data sources.

The study was further delimited by its focus on a specific time period, analyzing data collected from the 2018 to 2024 academic years. This temporal restriction excluded trends, policies, or changes in educational practices that occurred outside this timeframe. Moreover, the study emphasized quantitative data, particularly variables related to student demographics, academic, and non-academic performance. This quantitative focus enabled comprehensive statistical analysis but precluded the exploration of more qualitative factors, such as teacher perspectives or student narratives, which could have provided additional insight into the factors affecting graduation status among students with disabilities.

Definition of Terms

The following terms were used in this research study and were provided for consistency:

- *Data Mining Model:* A statistical model created by software that utilizes a specific set of techniques to extract hidden information from data (Coenen, 2011).
    - *Binomial Logistic Regression* – A statistical model used to predict the probability of an observation falling into one of two categories of a dichotomous dependent variable based on one or more independent variables (Laerd Statistics, n.d.).
    - *Neural Network* – A machine learning model designed to recognize patterns and make decisions by mimicking the structure and function of the human brain (IBM, n.d.-b; Paliwal & Kumar, 2009).

    - *Random Forest* – A machine learning algorithm that combines the predictions of multiple decision trees into a single result (IBM, n.d.-c).
    - *Support Vector Machine* – A supervised machine learning algorithm used for classification tasks to find an optimal line or hyperplane that best separates different classes or data points in an N-dimensional space (IBM, n.d.-a)
- *Student-Level Factors:* Characteristics specific to students' demographics, academic, and non-academic performance.
    - *Attendance* – A student's presence or absence during a given school day or class period, as recorded by the school's attendance system. For the purposes of the current study, attendance was classified as poor if a student was chronically absent, defined as missing 10% or more school days (GaDOE, n.d.-a).
    - *Behavior* – A student's conduct within the school environment, including actions that either align with or deviate from school expectations and policies. For the current study, behavior problems were measured by the number of discipline referrals a student received.
    - *Disability Classification* – The condition that most significantly impacts a person's daily life, encompassing impairments, activity limitations, and participation restrictions. It represents the disability that poses the greatest overall difficulty for the individual (NDS, n.d.).
    - *English Proficiency* – A student who is served in a language assistance program to help them attain English proficiency (DePaoli et al., 2015). For

the current study, English Learner status served as the indicator of English proficiency.

    - *Failed Classes* – Courses in which a student does not achieve the minimum required passing grade, resulting in a lack of earned credit. For the current study, failed classes were measured as the number of courses a student did not pass during their high school enrollment.
    - *Gender* – A demographic characteristic referring to a student's identification as male or female, as reported in school records.
    - *Grade Retention* – The assignment of a student to their current grade level for the following school year (GaDOE, 2014).
    - *Race and Ethnicity* – A demographic characteristic based on physical and cultural factors, including skin color, nationality, and language. In public schools, a student's race and ethnicity are typically identified by the enrolling parent or guardian (NCES, 1996).
    - *Socioeconomic Status* – An indicator of a person's financial, social, and educational resources, as well as their access to opportunities (NCES, 2015a).
- *School-Level Factors:*
    - *IEP Services* – A personalized written statement for a child with disabilities, detailing their academic and functional performance goals, special education services, assessment accommodations, transition plans, and rights upon reaching adulthood (Individuals with Disabilities Education Act, 2004).

        - *Collaborative Instruction* – Direct service is provided to a student with disabilities from a special education teacher in the regular education classroom for less than 100% of the segment (GaDOE, 2019).
        - *Consultative Service* – Direct service is provided to a student with disabilities by a special education teacher in the regular education classroom for the amount of time determined by the IEP team (GaDOE, 2019).
        - *Co-teaching Instruction* – Direct service is provided to a student with disabilities from the special education teacher in the regular education classroom for 100% of the segment each time the class meets (GaDOE, 2019).
        - *Direct Instruction* – Direct service provided to a student with disabilities by a special education teacher in a special education classroom (GaDOE, 2019).
        - *Supportive Service* – Additional services provided to a student with disabilities by personnel other than a special education teacher in the regular education classroom (GaDOE, 2019).
    - *Learning Environments* – The educational settings in which students receive instruction, which can vary based on the level of support and specialized services provided.

    - *Alternative School* – A separate school that addresses the needs of students who are not having success in the traditional educational setting (Lehr et al., 2003)
    - *General Education Classroom* – A "typical" classroom setting that may include both general education students and students with disabilities. In these classrooms, special education personnel may provide direct services to students with disabilities through consultative, collaborative, or co-teaching instruction. Additional supportive services may be provided to students with disabilities by personnel such as paraprofessionals, interpreters, and others (GaDOE, 2010).
    - *Special Education Classroom* – A classroom outside of the general education classroom, where students with disabilities receive direct services from a special education teacher (GaDOE, 2010).
    - *Separate Special Education School* – A separate school where a student with disabilities receives direct services from a special education teacher in a special education classroom in a separate school or program (GaDOE, 2019).
- *Student with a disability*: A child who has conditions such as intellectual disabilities, hearing or speech impairments, visual impairments, emotional disturbance, orthopedic impairments, autism, traumatic brain injury, other health impairments, or specific learning disabilities, and as a result, needs specialized education and related services (Individuals with Disabilities Education Act, 2004).

Outline of the Study

The current study, which focused on identifying factors associated with the eventual graduation status of students with disabilities, was divided into five chapters, along with a reference list and appendices. Chapter 1 introduces the problem, presents the problem statement for analysis, and outlines the purpose of the study. This chapter also includes the research questions, methodology employed, the study's significance, conceptual framework, assumptions, limitations, and delimitations. Additionally, a concise list of definitions of key terms was provided to ensure clarity throughout the study. Chapter 2 includes a comprehensive literature review, focusing on factors that may impact a student's graduation status, as well as the situation concerning students with disabilities and high school completion. An overview of the methodology used and the independent and dependent variables is discussed in Chapter 3 of the current study. The chapter elaborates on the study's population, sample, and the sampling procedures adopted. Furthermore, instrumentation, data collection, and data analysis are also described in this chapter. Chapter 4 presents the study's results, showing what the data reveal without interpretation. Chapter 5 presents the discussion and conclusions, interpreting the results in relation to the research questions, the literature, and the theoretical framework. It also highlights implications for practice, acknowledges limitations in data interpretation, and offers recommendations for future research and conclusions.

Chapter II

Literature Review

The literature review began by examining the potential outcomes of school dropout, both for the individual and for society. Understanding these impacts highlighted the need to address the problem and find effective solutions. The chapter continued by addressing the methods used to calculate graduation and dropout rates, as well as how these methods have been applied over the years. Finally, the literature review concluded by addressing the student- and school-level factors used as predictors of a student's graduation from high school. Dynarski et al. (2008) suggested that the “critical first step for preventing dropping out is understanding who is at risk of dropping out” by identifying both student-level and school-level problems before implementing interventions and reforms to address the issue (p. 12).

Consequences of Dropping Out

The failure to attain a high school diploma often leads to various adverse life outcomes, including poor health, as documented in numerous studies. Henry et al. (2012) conducted empirical research to explore the relationship between school disengagement, dropout, demographic factors, delinquency, and substance abuse. Their study used data from the Rochester Youth Development Study, which began collecting data in 1988, to investigate the effects of a school disengagement warning index. To test the different models employed in their study, they utilized a probit regression model to assess the effect of the school disengagement warning index on all variables.

Their analysis indicated that early school disengagement was positively associated with high school dropout rates (Henry et al., 2012). Specifically, as students accumulated more risk indicators, their likelihood of dropping out increased significantly (b = .47, SE = .04, $p < .05$). Additionally, school disengagement was positively associated with severe delinquency behaviors, including violent crime (linear b = .21, SE = .04, $p < .05$; quadratic b = -.06, SE = .02, $p < .05$), official arrest or police contact (b = .24, SE = .04, $p < .05$), and problem drug use (b = .22, SE = .08, $p < .05$). Moreover, Henry et al. (2012) noted that failure to graduate from high school was associated with poorer health outcomes compared to graduates.

Similarly, Andersen et al. (2021) conducted a study to explore the association between high school dropout rates and mental health. Utilizing survey data from the Danish National Youth Study in 2014, they categorized students into four distinct mental health groups: flourishing, moderate mental health, emotionally challenged, and languishing. These groups were tracked over a span of four years until either graduation or dropout occurred. Through the application of logistic regression models, Andersen et al. (2021) analyzed the correlation between students' mental health status and their eventual decision to discontinue schooling. The findings of the study revealed that the rates of school dropout were at their lowest among students exhibiting the fewest indicators of mental health issues (males: 8.4%, females: 4.4%), while the rates were highest among those demonstrating the most significant indicators (males: 21%, females: 13.3%) (Andersen et al., 2021).

A comprehensive analysis of the negative consequences associated with dropping out of school was conducted by Lansford et al. (2016). They found a strong correlation between the lack of education and health-compromising behaviors such as smoking, sedentary lifestyles, and obesity. The study, which tracked individuals from ages 5 to 27, aimed to establish connections among education, health, and factors influencing the relationship between dropping out of school and negative outcomes. The examined negative outcomes encompassed reliance on government assistance, unemployment, incarceration, drug use, and overall poor health. Lansford et al. (2016) concluded that, among their participants, dropouts were four times more likely to depend on government assistance, two or more times as likely to have used drugs, been unemployed, or reported poor health, three times more likely to have been arrested, and 24 times more likely to have experienced four or more of these outcomes.

The issue of unemployment and welfare dependency among high school dropouts was highlighted in a study by Garnier et al. (1997). Although this was not the primary focus of their research, which utilized data from a 19-year longitudinal study involving 194 families to analyze factors contributing to and the repercussions of dropping out of school, the study acknowledged the association between dropping out of school and negative societal outcomes. Apart from underscoring the prevalence of unemployment among dropouts, the study also emphasized that opportunities are notably limited even for those who secure employment within this demographic (Garnier et al., 1997).

Scanlon and Doyle (2021) conducted a phenomenological study using convenience sampling to select 31 students with disabilities transitioning from school to adulthood. Their research revealed that students with disabilities share similar aspirations as their non-disabled peers, including aspirations for employment. However, their research showed that the employment rate among individuals with disabilities aged 20 to

64 years was significantly lower at 49.7%, compared to 82.3% for individuals without disabilities (Scanlon & Doyle, 2021). Considering this disparity alongside findings from studies on employment for school dropouts, it is reasonable to infer that the likelihood of unemployment is even higher for students with disabilities who drop out compared to the general population.

High school dropouts represent the least educated segment of the labor market, leading to significantly bleak job prospects and lower wages than those of individuals with higher levels of educational attainment (Rumberger, 2011). The lack of promising employment opportunities significantly reduces the potential lifetime earnings of dropouts compared to those of their high school graduate counterparts. In 2008, it was reported that dropouts earned, on average, $9,000 less annually than graduates, resulting in approximately $260,000 in lost income over a lifetime (Dynarski et al., 2008). Adjusted for inflation, this income gap equates to $12,880 today or an astounding $372,089 over a lifetime (Webster, n.d.). Due to limited job opportunities, the financial implications of dropping out extend beyond the immediate years, leading to substantial lifetime income losses compared to graduates.

Other researchers who recognized the dire economic consequences of dropping out of high school were Freeman and Simonsen (2015). In their literature review, they examined intervention practices aimed at addressing high school dropout and completion rates. Through their exploration, they highlighted limited job opportunities as one of the key factors driving the need for interventions. As the demand for a more educated workforce continues to rise, the economic and social consequences of high school dropout rates become increasingly pronounced (Freeman & Simonsen, 2015).

In addition to the adverse outcomes experienced by individuals, high school dropouts also exert extensive negative effects on society, manifesting in various consequences such as a loss of national income, reduced tax revenues, increased expenditures on crime prevention and punishment, and increased burdens on the welfare system (Dunn et al., 2004; Prevatt & Kelly, 2003). Dunn et al. (2004) conducted a study examining 228 students with learning disabilities (LD) and mental retardation (MR) who dropped out and 228 students with LD and MR who did not drop out to analyze factors that may predict dropout. Alongside investigating factors that may influence a student to drop out, they highlighted the economic and social repercussions for society associated with dropouts, citing the Institution for Educational Leadership's estimate that dropouts cost the national economy billions of dollars in lost revenue and increased social services, including the criminal justice system, lost wages, and poor health (Dunn et al., 2004).

Prevatt and Kelly (2003) also recognized the societal impacts of dropouts in their literature review on dropout prevention for school-aged children. While focusing on methodological concerns and intervention programs, they discussed the negative consequences of dropping out of school. Specifically, they highlighted societal effects, including forgone national income, decreased tax revenues, increased demand with reduced financial support for government services, heightened crime levels, and poor health outcomes. Thus, they emphasized the importance of addressing the dropout issue and identifying preventive measures (Prevatt & Kelly, 2003).

The combination of reduced potential among dropouts and the societal costs they generate leads to detrimental consequences for the broader community. Sum et al. (2009) quantified the net fiscal contribution of high school dropouts as a loss of $5,200 per year, contrasting starkly with the positive net fiscal contribution of $287,000 from graduates. Beyond the fiscal impact, each high school dropout incurs an estimated cost of approximately $292,000 more to the United States over their lifetime compared to high school graduates. This cost encompasses factors such as lower taxable income, incarceration, and heightened reliance on social welfare programs (Sum et al., 2009).

Conversely, Rumberger and Lim (2008), in their comprehensive review spanning 25 years of research on reasons for student dropout, stated that a high school graduate yields more than $200,000 in government savings. These savings are attributed to increased tax contributions, decreased public assistance expenditures, reduced healthcare costs, and lower criminal justice expenses. Drawing on estimates of government savings associated with graduates, reducing dropout rates by 50% within a single cohort can yield over $45 billion in savings for society (Rumberger & Lim, 2008).

Moreover, if half of the students graduate rather than drop out, there are additional economic benefits. Tucci (2011) conducted a study estimating that these economic benefits, encompassing increased annual earnings and additional job creation, could total $7.6 billion. The combination of savings and increased earnings resulting from graduating more students and curbing dropout rates would significantly contribute to overall economic well-being. Hence, a comprehensive understanding of the definitions and calculations underlying graduation and dropout rates is crucial for formulating effective strategies to increase graduation rates and reduce dropout rates.

Graduation Rates

According to Rumberger (2011), the three primary types of graduation rate definitions are *status*, *event*, and *cohort*. Each type of graduation rate measures the percentage of individuals in a population who successfully graduate, with distinctions arising from the time periods considered. The *status rate* assesses a specific point in time; the event rate covers a specified time frame, typically a year; and the cohort rate spans a longer period, usually four years from the beginning of ninth grade to the end of the 12th grade (Rumberger, 2011). These divergent calculation methods led to disparities in reported graduation rates across states, as revealed by federal accountability mandates.

In 2001, the federal No Child Left Behind Act (NCLB) ushered in an era of educational accountability, mandating high school completion for all students, including students with disabilities, economically disadvantaged students, and English language learners (Reschly & Christenson, 2006). However, as schools nationwide sought to meet NCLB requirements, it became evident that states employed diverse data-collection methods, leading to a lack of standardized procedures for calculating dropout rates (Christle et al., 2007). This discovery was definitively established in 2003, when the Civil Rights Project survey revealed no meaningful accountability for graduation rates in most states (Hauser & Koenig, 2011). These variations in data-collection methods, coupled with differing definitions of graduation rates, contributed to discrepancies across states.

The National Governors Association (NGA) established the Task Force on State High School Graduation Data in 2005 to develop more consistent and accurate reporting (Hauser & Koenig, 2011). This task force introduced a standard four-year adjusted cohort graduation rate known as the NGA Grad Rate. Within three years, Margaret Spellings, the then Secretary of Education, issued new guidelines for the NCLB Act to establish a uniform measurement of graduation rates. Despite these efforts, the challenge of non-standardized graduation rate calculations persisted until 2011, when the U.S. Department of Education introduced the Adjusted Cohort Graduation Rate (ACGR), offering a uniform measurement standard across states (DePaoli et al., 2018). To calculate this cohort graduation rate, a fraction is constructed, with the numerator representing the count of students who graduated within four years with a regular high school diploma. The denominator represents the total number of students in the graduation cohort, adjusted for transfers, emigrations, or student deaths. The graduation cohort comprises all students who entered ninth grade for the first time four years prior to the current year. It is essential to note that the primary distinction between the NGA Grad Rate and the ACGR lies in the type of diploma that is permitted. The ACGR only counts a general education diploma as a valid graduation credential (Hauser & Koenig, 2011).

The introduction of NCLB and the increased scrutiny of accountability for subgroups, including students with disabilities, required school districts to reevaluate their strategies for helping all students attain a high school diploma. Prior to NCLB, accountability requirements for students with disabilities primarily focused on their Individualized Education Program (IEP) and the school's demonstration of compliance with these customized plans (McLaughlin & Thurlow, 2003). NCLB ushered in accountability based on the academic achievement of all students, including those with disabilities. Another pivotal piece of federal legislation aimed at supporting students with disabilities was the Individuals with Disabilities Education Improvement Act (IDEA) (U.S. Department of Education, 2004). The accountability measures stipulated in both NCLB and IDEA mandated an increase in graduation rates, accompanied by a concurrent reduction in achievement gaps among students with disabilities (Pyle & Wexler, 2012).

Graduation rates among students with disabilities were examined by Elbaum et al. (2014) to assess the impact on district accountability. Analyzing data from 67 Florida school districts, they found that an increase in the number of students with disabilities did not correlate with lower overall district graduation rates. However, they noted a statistically significant association between the percentage of students with disabilities who were Black or Hispanic and lower graduation rates. This finding may be attributed to the disproportionate representation of minorities in special education, particularly in categories such as intellectual and emotional disabilities, which are associated with the lowest graduation rates among all disabilities (Elbaum et al., 2014).

Notably, the overall public high school graduation rate for students with disabilities in the United States improved markedly, reaching 70.6% in 2020, up from 62% in 2013 (NCES, 2015b, 2021b). While this progress is commendable, it is crucial to acknowledge that, despite the improvement, the graduation rates for students with disabilities still lag behind the national average for all students, which was 86% in 2020 (NCES, 2021b). Given the ongoing monitoring of schools and districts by state and federal authorities, with graduation rates as a key metric, continued vigilance in monitoring this metric for all students and subgroups is imperative. This ensures that efforts to improve educational outcomes for students with disabilities, as well as other underserved populations, remain a primary focus.

Graduation rates are one of the primary metrics used by schools, districts, and states. Another metric used is dropout rates. While these two metrics measure the same student population, the two rates do not directly relate to each other. As explained by Rumberger (2011):

> Students who drop out can still graduate at a later time, while students who never quit school still may not graduate. To graduate, students must earn a high school diploma, but some students earn alternative diplomas by taking state or national examinations. Students who earn these alternative diplomas are not considered graduates, but they also are not considered dropouts. (p. 2)

The differences between graduation rates and dropout rates necessitate distinct calculations for each.

Dropout Rates

As with graduation rates, dropout rates are also defined in three different ways: *status*, *event*, and *public school event* dropout rates (Rumberger, 2011). The *status dropout rate* refers to the percentage of the population, typically aged 16 to 24, who are neither enrolled in nor have completed school. The *event dropout rate* measures the percentage of the population, typically ages 15 to 24, who dropped out of the 10th through 12th grade in the previous year. This is the dropout rate most often used to measure dropout rates among students with disabilities (U.S. Department of Education, n.d.). The *public school dropout rate* is based on the percentage of public school students who dropped out of high school in the previous year. These calculations, in 2008, produced dropout rates of 8%, 3.5%, and 4.1%, respectively (Rumberger, 2011).

For over six decades, the primary source for calculating dropout rates was the Current Population Survey (CPS), conducted by the U.S. Census Bureau (Hauser & Koenig, 2011). This method involved monthly household surveys to identify individuals aged 16 to 24 who were not enrolled in school and had not graduated. Given the limited options available at the time, this approach was considered the most reliable method for assessing educational attainment. However, due to its household-based nature, the data could not be further disaggregated beyond the regional level, as it was challenging to link respondents to specific schools.

A shift in data collection methods occurred in the 1960s, when data were collected through the Common Core of Data (CCD) by the U.S. Department of Education's National Center for Education Statistics (NCES), which obtained information directly from schools (Hauser & Koenig, 2011). The data allowed for disaggregation at the state and local levels, but lacked sufficient granularity at the student level, primarily due to issues related to student mobility and grade retention. The data collected using CPS and CCD methods showed significant differences from each other and from other state-specific calculation methods. These variations resulted from differences in data collection processes, treatment of General Education Development (GED) recipients, the types of schools included in the reports, and the calculation methods applied.

Despite variations in data collection methods, one consistent trend emerged: dropout rates improved over the years. Using the CCD method, the overall dropout rate in the United States decreased from 7.4% to 5.3% between 2010 and 2020 (NCES, 2022). Concurrently, the dropout rates among students with disabilities exhibited a declining trend over the same decade, falling from 21.1% in 2010 to 16.6% in 2019 (U.S. Department of Education, 2021). Although these data points highlight improvements in dropout rates for students with disabilities over the past decade, it remains imperative to underscore that, when compared to the overall dropout rates in the United States, there is still room for further progress and improvement, which requires a deeper understanding of the underlying factors influencing students' decisions.

Student-Level Factors

Preventing student dropout is a shared objective for all educators. To effectively work towards this goal, it is crucial to understand not only the dropout data trends but also the additional factors influencing a student's decision to drop out. While some factors have uniform effects on all students, others exhibit different impacts on students with disabilities compared to their peers in the general population (Bear et al., 2006; Kortering et al., 1992; Zablocki & Krezmien, 2013). The following exploration of student-level factors is drawn from the literature review, illuminating their impact on student dropout rates.

Demographics

Demographic characteristics, such as disability classification, English proficiency, gender, race and ethnicity, and socioeconomic status, significantly influence academic performance and dropout rates among both students with disabilities and their general education peers. Ritter's (2015) issue brief examined factors contributing to on-time high school graduation, with a particular focus on the state of Washington, and identified demographic characteristics as key indicators of dropout risk. Through a comprehensive review of recent studies, she examined the characteristics of students most likely to drop out of school early. Among the various factors analyzed, demographic considerations proved to be a critical area of investigation.

The analysis of demographic data yielded noteworthy trends. One striking finding was the gender disparity, with males exhibiting a dropout rate 3.5% higher than their female counterparts. Additionally, the research highlighted disparities among racial and ethnic groups, revealing that Asian students had the lowest dropout rate at 6%, while American Indian students faced the highest dropout rate at 26.6% (Ritter, 2015). These statistics underscored the importance of considering demographic factors in understanding the dynamics of high school dropout. More specific details regarding each demographic variable are discussed accordingly.

Disability Classification. The primary disability classification served as a crucial variable in the investigation conducted by Dunn et al. (2004), which focused on students with LD and MR, both classified as mild disabilities. They noted that students with mild disabilities face a heightened risk of dropout compared to those with more severe disabilities. Among the four variables examined in their study, primary disability classification was the only factor significantly impacting the statistical model. The impact of primary disability classification varied across different disabilities; students with LD exhibited a substantially higher likelihood of dropping out (58%) compared to those with MR (37%). In the dropout sample, 71% of students were identified as having LD, while 29% were identified as having MR (Dunn et al., 2004).

Reschly and Christenson (2006) conducted a study to investigate the engagement levels of students with mild disabilities compared to their typically achieving peers, as well as their rates of school completion. They defined mild disabilities as encompassing learning disabilities and emotional or behavioral disorders. They identified students with disabilities as particularly vulnerable to school dropouts. Utilizing a multivariate analysis of variance (MANOVA), they analyzed unweighted samples comprising 1,498 students with mild disabilities and 6,897 typically achieving students. Although this analysis yielded significant comparisons, the effect size on all engagement variables was small. Subsequently, employing logistic regression to compare various study variables, Reschly and Christenson (2006) found that their model correctly classified 77% of students with LD who either dropped out or completed high school, 70.7% of students with emotional or behavioral disorders (EBD), and 84% of students without disabilities. Overall, the findings of this research revealed substantial variations in dropout rates among students with different disabilities, with the highest rates observed among those categorized with EBD and learning disorders (LD) (Reschly & Christenson, 2006).

Zablocki and Krezmien (2013) also investigated the impact of primary disability classification and other factors on school dropout rates among students with disabilities. Using the National Longitudinal Transition Study 2 (NLTS2) data, they analyzed predictors of dropout using logistic regression with primary disability classification, demographics, and emotional engagement. Their analysis indicated that students with EBD experienced a dropout rate of 26.7%, in stark contrast to students with low-incidence disabilities, including autism, multiple disabilities, hearing impairment, orthopedic impairments, visual impairments, traumatic brain injury, and deaf/blindness, who exhibited a notably lower dropout rate of 4.6% (Zablocki & Krezmien, 2013).

In their studies, both Reschly and Christenson (2006) and Zablocki and Krezmien (2013) concluded that primary disability classification alone was not a key indicator of a student's likelihood of dropping out of high school. Nevertheless, it is noteworthy to examine the variations in dropout rates among different disabilities. Recent data reported by the U.S. Department of Education (2021) presented current and historical dropout rates for students, categorized by disability. Table 1 outlines the percentages spanning from 2010 to 2019.

Table 1

Dropout Rates by Disability 2010 to 2019

Disability	2010	2019
Autism	6.6%	6.7%
Deaf/Blind	13.3%	8.8%
EBD	38.7%	32.9%
Hearing Impaired	10.2%	7.8%
Intellectual Disability	19.2%	13.9%
Multiple Disabilities	13.9%	13.4%
Orthopedic Impairment	12.4%	7.4%
Other Health Impairment	19.1%	17.5%
Specific Learning Disability	20.2%	16.0%
Speech	17.0%	11.3%
Traumatic Brain Injury	12.5%	9.8%
Visual Impairment	8.4%	7.9%

Note. Adapted from *43rd annual report to Congress on the implementation of the Individuals with Disabilities Education Act*, by U. S. Department of Education, 2021, https://sites.ed.gov/idea/files/43rd-arc-for-idea.pdf

The figures in this table indicate that, while primary disability classification alone is not the sole predictor of a student's decision to drop out, variations in dropout rates across disabilities are notable. Given the manifestations of these students' disabilities in both learning and behavior, it is plausible that other potential indicators are more prevalent.

English Proficiency. English Learner (EL) Status is the indicator of English proficiency in the current study. In a report for the California Dropout Research Project, Callahan (2013) acknowledged California's substantial enrollment of English Learner (EL) students, encompassing more than one-third of the total national population. Upon enrollment, EL students undergo an English proficiency screening, with their progress in English language acquisition monitored annually. Upon demonstrating proficiency, these students transition from being classified as ‘current’ EL students, who receive English language services, to ‘former’ students who are monitored but no longer receive such services. Given that current EL students constitute approximately 11% of Kindergarten through twelfth-grade enrollments nationwide, and current and former EL students together account for around 20% (Callahan, 2013), it becomes imperative to understand and address issues pertaining to EL student dropout rates.

The number of students in the United States classified as English Learners is on the rise (NCES, 2023c). In 2010, there were 4.5 million English Learners in public schools, constituting 9.2% of the total public school student population. By 2020, this figure had increased to 5 million, representing 10.3% of the public school student population. With this upward trend, it is imperative to ensure that school systems are attuned to the unique needs of these students and implement strategies and services essential for their academic success. Compared to the national average graduation rate of 87% in 2020, English Learners exhibited a lower average graduation rate of 71% (NCES, 2023b). However, it remains unclear whether being an English language learner is a direct indicator of a student’s ultimate graduation or decision to drop out. A study by Wood et al. (2017) used data from the Education Longitudinal Study of 2002 and included over 14,000 students across 684 public and private schools. Their findings indicated that being an English learner was not a significant predictor of dropout rates when controlling for other variables in the study. It is plausible that other factors, such as the observation that nearly half of the nation’s Latino students attend high schools characterized by high poverty rates (Balfanz & Legters, 2006), exert a more substantial influence on the eventual outcomes of these students.

Gender. Research suggested that gender influences academic performance and dropout risk. Wagner et al. (2006) found that, in the general education population, female students outperformed male students academically. While these gender-based differences in academic performance are less pronounced among students with disabilities, it is worth noting that in the NLTS2 study, the students with disabilities group comprised two-thirds males and one-third females. Of these students with disabilities, males accounted for a significantly higher proportion of categories such as autism and emotional disturbances (Wagner et al., 2006).

In their comprehensive analysis of the reasons behind high school dropout rates, McDermott et al. (2019) conducted a mixed-methods study to explore how various factors impact male and female students differently. While gender alone did not emerge as a direct determinant of dropout, the research shed light on the differential influences experienced by males and females. Using chi-squared tests with a Bonferroni correction of $p < .0013$, there was a statistically significant difference in reasons for dropping out by sex ($X^2(38) = 137.75$, $p < .0001$). Females were found to be more susceptible to leaving school due to a range of factors, including mobility issues, peer influences, health-related concerns, involvement in criminal activities, and other categories. Specifically, females faced heightened risks associated with pregnancy, bullying, family conflicts, academic struggles, and dissatisfaction with school, with health-related issues being cited as the primary reason for leaving school by 26.4% of females compared to 9.8% of males. Conversely, males were more likely to drop out due to family-related challenges and issues related to school engagement and environment, such as boredom, perceived irrelevance of schooling, the need to support their families through work, disciplinary issues, and academic difficulties. Notably, 62.3% of males cited engagement and environmental factors as reasons for leaving school, compared to 44.9% of females. While gender alone did not emerge as a causal factor for dropout, the distinct differences in the factors influencing males and females underscored the complexity of the dropout phenomenon (McDermott et al., 2019).

Race and Ethnicity. Graduation rates exhibit variability across different ethnic and racial groups. Murnane (2013), in his analysis of United States graduation rates, found that the estimated graduation rates for White, Black, and Hispanic students between 1986 and 1990 were 86.3%, 78.2%, and 77.8%, respectively. In comparison, the NCES (2021) reports more recent graduation rates for these same groups as 90%, 81%, and 83%, respectively. However, significant gaps remain.

Notably, within the Hispanic subgroup, there is a large discrepancy between those born outside the United States and first-generation Hispanic youth, with almost one-third as many graduates among those who immigrated as among U.S.-born students (Shannon & Bylsma, 2006). While graduation rates for each racial subgroup have improved over this time span, the gap between the groups persists.

While demographics constituted just one facet of the inquiry, the statistics presented in Ritter's brief provided valuable insights into the complex landscape of high school dropouts (Ritter, 2015). By exploring the differential experiences of various demographic groups, the brief contributed to a deeper understanding of the challenges faced by students at risk of dropping out and informed efforts to improve graduation rates and promote educational equity.

Socioeconomic Status. Students' socioeconomic status (SES) is annually determined based on their eligibility for free or reduced-price lunch (Blazer & Gonzalez Hernandez, 2018; GaDOE, n.d.-c). This status can fluctuate throughout a student's high school career, but the recorded status in their dropout or graduation year is utilized for that specific year's measurements. As with other factors influencing students' decisions to stay in school or not, it is challenging to pinpoint a single factor as the sole reason a student chooses to leave school without graduating.

In their literature review, primarily focused on Norwegian and Nordic studies, Ramsdal and Wynn (2022) investigated the dropout process and the challenges students may encounter that may contribute to this outcome. While their research revealed no single factor explaining dropout, their review of Organization for Economic Co-operation and Development (OECD) reports highlighted the overrepresentation of students from disadvantaged backgrounds in dropout rates (Ramsdal & Wynn, 2022).

In 2015, the National Center for Education Statistics (as cited in Blazer & Gonzalez Hernandez, 2018, p. 1) reported a dropout rate of 9.9% for students in the lowest-income bracket, compared to 2.4% for those in the highest-income bracket. Among students completing high school in the 2019-2020 school year, the percentage of economically disadvantaged students who graduated was 81%, which is below the national average of 87% (NCES, 2023b). This suggests that socioeconomic status may influence the likelihood of dropping out.

According to Swanson (as cited in Elbaum et al., 2014, p. 4), graduation rates decrease by 3.8% for every 10% increase in the number of students eligible for free or reduced lunch. Elbaum et al. (2014) observed in their study of 67 Florida school districts that the graduation rate declined by 0.59% for the same increase in free- and reduced-lunch eligibility. However, in the same districts, the decrease among students with disabilities was closer to 6%, nearly double the average decrease noted by Swanson. These findings suggested that while socioeconomic status affects graduation rates of all students, it has nearly double the impact on students with disabilities.

In her Ballard issue brief, Bradley (2022) highlighted the enduring achievement gap faced by lower-income students, attributing it to the adverse effects of poverty on brain development, inadequate resources in underfunded schools, and a shortage of quality teachers in these settings. This achievement gap is closely associated with higher dropout rates: students from low-SES backgrounds drop out at 7.2%, compared to 3.6% for middle-SES students and 3.9% for high-SES students. Notably, the recognition of this achievement gap dates back as early as 1930, and despite decades of attention, there has been little progress in narrowing it. Furthermore, this phenomenon is not unique to the United States; studies from around the world also demonstrate the pervasive nature of the achievement gap across various socioeconomic contexts.

Wagner et al. (2014) used NLTS2 data to examine the effect of socioeconomic status on the likelihood of high school graduation among students with disabilities. A logistic regression analysis was conducted using income level as the independent variable, categorized into two groups: annual income less than $25,000 and annual income between $25,000 and $50,000. The dependent variable was high school graduation status. For students in the lower income category (less than $25,000), the odds of graduating from high school were significantly lower compared to a reference group earning $50,000 or more (*OR* = 0.41, 95% *CI* [0.37, 0.45]). Students in the $25,000 to $50,000 income category also had lower odds of graduating than the reference group (*OR* = 0.68, 95% *CI* [0.61, 0.75]). This finding indicated that both income categories are associated with a decreased likelihood of graduating, with the lowest income category showing the most significant effect. When additional covariates were included to control for potential confounding factors, the *R*-squared value was 0.09, suggesting that income levels and the included covariates account for approximately 9% of the variability in high school graduation. While socioeconomic status is significant, the majority of the variance (91%) remains unexplained, underscoring the need to investigate other factors that influence graduation rates among students with disabilities (Wagner et al., 2014).

Academic Performance

Various metrics are employed to assess poor academic performance in students. Rumberger and Lim's (2008) comprehensive review of 203 studies revealed three primary indicators of academic performance across different grade levels: test scores, grades, and failed classes. Test scores and grades are commonly used to evaluate academic performance across all grade levels. While test scores provide a snapshot of a student's abilities at a specific moment, grades offer a more comprehensive assessment by reflecting a student's ability and effort over time. Grades encompass factors such as homework completion, participation, test performance, and overall assignment completion, making them more consistent predictors of academic success or failure (Rumberger & Lim, 2008). Moreover, in middle and high school, course failures emerge as significant predictors of dropout likelihood. Students who fail entire courses demonstrate a lack of progression toward fulfilling academic requirements, raising concerns about their ability to complete educational programs. Consequently, students who experience course failures face a heightened risk of dropping out of school (Rumberger & Lim, 2008).

Another measure of academic performance concerns literacy. A study by Daniel et al. (2006) explored the relationship between adolescent reading ability and the risks of school dropout and suicidality. Screening 1062 fifteen-year-old students in six public high schools in the southeastern United States, they classified 148 students as poor readers and 914 students as typical readers. Out of these students, 94 from each reading category were selected and agreed to participate in the study. After the initial assessment, students were interviewed annually, with one interview item asking whether they were still in school. Univariate analysis indicated a substantially higher dropout rate among students with poor reading abilities ($OR = 7.18$, $SE = 3.93$, $p < .001$), with 30.2% of them dropping out of school, compared to only 5.1% of students with typical reading skills. When other factors were considered using multivariate analysis, the results remained consistent. Thus, poor reading skills are associated with a higher likelihood of school dropout (Daniel et al., 2006).

Regardless of the measurement employed, it is essential to acknowledge that poor academic performance is one of the most robust predictors of not completing high school (Rumberger, 2011). In his book, Rumberger (2011) discussed the importance of academic success throughout different grade levels, drawing on a Baltimore study. According to the study, early academic success is paramount, as students who failed and were retained in first grade were seven times more likely to drop out than their non-retained peers, and students retained in middle school were 10 times more likely to drop out. Citing a 2005 study of Chicago Public Schools, Rumberger (2011) noted that students who did not fail courses or get retained were three and a half times more likely to graduate than students who failed courses and were retained. Based on the current study and others in his book, Rumberger (2011) emphasized that academic achievement, particularly during high school, stands as the foremost predictor of a student's probability of dropping out or graduating.

In a study by Scanlon and Mellard (2002), the experiences of high school dropouts were examined both before and after deciding to withdraw from school. Participants were categorized into four groups: 1) LD and EBD dropouts who obtained a GED; 2) dropouts without an identified disability enrolled in an adult education program aiming to obtain a GED; 3) LD and EBD dropouts enrolled in an adult education program aiming to obtain a GED; and 4) currently enrolled high school students with LD and EBD (Scanlon & Mellard, 2002). The interviews revealed a recurring theme among students with LD. They frequently identified academic difficulties related to their learning disabilities as the main factor influencing their decision to drop out.

Another significant finding in Scanlon and Mellard's (2002) research highlighted reading as the academic skill most frequently affected by learning disabilities. As emphasized by Kortering et al. (1992), a "student who fails to develop reading skills is at a distinct disadvantage in trying to succeed or survive in the school setting" (p. 423). Multiple studies have shown that school dropouts are more likely to exhibit reading deficiencies, which, when combined with other factors, can accurately identify future dropouts (Kortering et al., 1992; Scanlon & Mellard, 2002). The findings in the studies conducted by both Scanlon and Mellard (2002) and Kortering et al. (1992) underscored the critical importance of providing services and support to students with learning disabilities, particularly in the area of reading. Providing assistance in this domain can play a crucial role in helping these students overcome the challenges associated with their disabilities and promoting their academic success.

In a report by Wagner et al. (2006), academic performance, particularly among students with disabilities, was investigated using NLTS2 data. A significant achievement gap was found in reading, mathematics, science, and social studies between students with disabilities and their general education peers, with the highest disparity in reading comprehension. There are many factors that can contribute to poor academic performance, including demographic factors, household characteristics, and school experiences. The NLTS2 investigated academic performance through a multivariate analysis of these factors and found that it is vital to consider the whole student, rather than just individual characteristics, to help them succeed (Wagner et al., 2006).

While poor academic performance is commonly associated with increased dropout rates, students with disabilities often exhibit lower academic achievement compared to their peers in general education. Despite this correlation, Bear et al. (2006) utilized a MANOVA to analyze measures of academic ability and self-perceived reading ability. Surprisingly, their findings revealed no significant difference in academic performance ($F(4,71) = .086$, $p > .05$) or in self-perceptions of reading ability ($F(3,72) = 1.34$, $p > .05$) between learning-disabled students who completed high school and those who dropped out. This suggests that factors beyond academic performance may influence a student's decision to leave school prematurely. Given that students with learning disabilities consistently rank among the highest in terms of dropout rates, it becomes evident that additional variables must be considered to fully understand the complexities of dropout behavior.

Building on these findings, Bowers et al. (2013) conducted a comprehensive review of research on dropout indicators. They emphasized the predictive strength of the *ABC indicators*: attendance, behavior, and course performance. Their review concluded that combining these indicators in multivariate models yields stronger predictive power than analyzing them in isolation. Similarly, Knowles (2015) developed a statewide early warning system in Wisconsin that used a combination of academic, behavioral, and demographic factors to identify students at risk of dropping out. Knowles demonstrated that relatively simple, interpretable predictors, such as course failures, attendance patterns, and disciplinary incidents, can be effectively utilized within logistic regression models to provide accurate and scalable predictions for educators and policymakers.

Extending this line of research, Kotsiantis (2009) applied educational data mining techniques to predict students at risk of dropping out. Using real-world educational data, Kotsiantis demonstrated that machine learning algorithms can successfully identify students at risk of dropping out by analyzing their academic performance, attendance, and demographic variables. The study emphasized the value of predictive modeling for early intervention, noting that accurate identification of at-risk students enables educators to implement targeted support strategies before students disengage from school completely. The inclusion of insights from Bowers et al. (2013), Knowles (2015), and Kotsiantis (2009) underscored the importance of examining multiple, interrelated factors when investigating dropout risk, thereby supporting the present study's approach in using both student-level and school-level variables to model graduation outcomes for students with disabilities.

Non-Academic Performance

Two decades ago, Alexander et al. (1997) conducted a longitudinal study in Baltimore to explore the primary factors contributing to student dropout. Employing a representative random sampling method, they tracked students from 20 elementary schools from first grade through high school graduation or dropout. Data collection began in the ninth year of the study and continued through the fourteenth year, primarily through self-reported information from the participants. The findings revealed that 31.4% of the student cohort dropped out, 47.2% graduated, 14.1% could not be located once they reached high school, and 7.3% were still enrolled at the time of their last contact (Alexander et al., 1997). Through logistic regression analysis of student-level factors and predictor clusters, the study identified student engagement, established through school experiences and interactions as early as first grade, as one of the primary determinants of dropout.

Student engagement encompasses various dimensions, including academic, behavioral, psychological, and cognitive aspects (Reschly & Christenson, 2006). Among these, behavioral engagement is the most readily observable and documented in educational settings, often manifested through negative behaviors and poor attendance (S. J. Dekle, personal communication, March 28, 2024). Findings from a survey of student dropouts by Bridgeland et al. (2006) revealed that 47% of dropouts cited boredom as a reason for leaving school, while 59% to 65% faced attendance issues before ultimately dropping out of school. More specific details regarding each non-academic performance are discussed accordingly.

Attendance. Student engagement was also reviewed in Ritter's (2015) issue brief, where attendance was identified as a key indicator of engagement and, ultimately, graduation. In this brief, Ritter's research uncovered that poor attendance patterns that begin in middle school often worsen in high school and can ultimately lead to low motivation and academic difficulties. When students are absent and miss learning opportunities, they often struggle academically, which can lead to them dropping out of school. Although attendance was just one of the factors examined by Ritter (2015), it was determined to be a key indicator for identifying students at risk of dropping out.

Using data from Miami-Dade County Public Schools, Blazer and Gonzalez Hernandez (2018) reviewed the characteristics of students who had the highest likelihood of dropping out. Like Ritter, they used absenteeism as a sign of student disengagement from school. They examined data on chronically absent students to determine how this characteristic affected the students' decision to remain in school. Their study showed that students who were chronically absent in any school year beginning in 8^{th} grade were between 6.6 and 8.6 times more likely to drop out than students not identified as chronically absent. This percentage grows if a student is chronically absent for multiple years (Blazer & Gonzalez Hernandez, 2018).

Regardless of the student-level factors examined in determining students' successful completion of high school, it is evident that these factors alone are insufficient for predicting graduation or dropout rates. It is also essential to consider external influences that may impact students' decisions. The school students' attendance plays a significant role in the quality of education they receive and can potentially affect their likelihood of graduating. Therefore, it is crucial to examine school-level factors as well.

Behavior. Behavioral engagement was further explored in a nationwide survey by McDermott et al. (2019), which uncovered significant associations between absences, suspensions, expulsions, and students' decisions to drop out of school. This mixed-methods study further revealed that behavioral issues, whether within or outside the school environment, were associated with an increased likelihood of dropping out. Although the study did not specifically target students with disabilities, it underscored the robust correlation between behavior and dropout risk, implying that students facing behavioral challenges due to disabilities are particularly vulnerable to dropout compared to their peers (McDermott et al., 2019).

Students with emotional or behavioral disorders consistently exhibit the highest percentage of dropouts among various disabilities (Bellis, 2003; U.S. Department of Education, 2021). These students, by definition, exhibit behavioral issues in school, resulting in disruptions to instruction through time spent in the office, suspensions, and expulsions. Beyond the instructional loss, when students are suspended or expelled, the odds of dropping out increase significantly, with the odds of grade retention also experiencing a notable increase (Zablocki & Krezmien, 2013). It is important to note that students with EBD are not the sole population grappling with behavior issues in school.

Additionally, research suggested that students with learning disabilities typically also tend to experience more behavior problems than their non-disabled peers (Bear et al., 2006). This underscored the pervasive impact of behavior challenges on academic outcomes and dropout rates across diverse student populations. Understanding the relationship between behavior issues and dropout risk is crucial for implementing targeted interventions and support strategies to address the needs of students with emotional or behavioral disorders, as well as those with learning disabilities, in order to promote academic success and graduation.

School-Level Factors

In addition to student-level factors, various school-level factors play a significant role in students' decisions to persist in their education until graduation. In their literature review, Ecker-Lyster and Niileksela (2016) examined studies that delved into characteristics of schools attended by students, moving beyond student-level factors. These studies explored various aspects, including school size, students' socioeconomic backgrounds, grade retention and suspension rates, administrators' experience, school climate, student-teacher ratios, and teacher turnover. A common theme emerged despite the diversity of factors investigated: Lower student-teacher ratios were consistently associated with higher graduation rates across the reviewed studies (Ecker-Lyster & Niileksela, 2016). In the current study, school-level factors include IEP services and learning environments. More specific details regarding each school-level factor are discussed accordingly.

IEP Services

Students with disabilities navigate an educational landscape shaped by various school-level factors designed to meet their diverse needs. According to the GaDOE (2019), these factors include specialized services and learning environments that provide tailored support to accommodate students with disabilities. These services include collaborative instruction, consultative service, co-teaching instruction, direct instruction, and supportive services. In general education classrooms, students with disabilities may receive supportive services, such as additional assistance from personnel other than a special education teacher; collaborative instruction and co-teaching, where a certified special education teacher assists either part-time (collaborative) or full-time (co-teaching); and consultative services, where a special education teacher provides guidance for a designated period determined by the IEP team. In contrast, special education classrooms serve only students with identified disabilities, where instruction is delivered directly by a special education teacher (GaDOE, 2019). These personalized services and learning environments aim to foster academic success by ensuring student with disabilities receive the necessary support to thrive in their educational journey.

Learning Environments

In most school districts, students have access to various learning environments, with the general education classroom being the most prevalent. Placement for students with disabilities is determined by the IEP team, which is tasked with maximizing the inclusion of students with disabilities in classrooms alongside non-disabled peers to the greatest extent feasible (GaDOE, 2010). This guiding principle, known as the Least Restrictive Environment (LRE), emphasizes the importance of providing students with disabilities the opportunity to learn and interact with their non-disabled peers as much as possible. A statement outlining how a student will receive services in the LRE is a mandatory component of every IEP (Kurth et al., 2019). The IEP process involves collaborative planning among educators, parents or guardians, and other relevant stakeholders to ensure that each student’s unique needs are effectively addressed within the educational setting.

The general education classroom is identified as the least restrictive environment, providing students with disabilities the opportunity to learn alongside their non-disabled peers and participate in the same curriculum to the fullest extent possible (GaDOE, 2019). In contrast, a separate special education school is considered the most restrictive, often catering to students with more significant disabilities who require specialized instruction and support (GaDOE, 2019). The environment in which students with disabilities are served must be reported to the state annually to ensure compliance with regulations and to monitor the provision of appropriate services (Kurth et al., 2019). While each of these settings serves a crucial purpose for different students, they collectively contribute to the overarching goal of ensuring that all students, regardless of ability or disability, receive a quality education tailored to their individual needs.

Alternative School. Not all students thrive in the conventional school environment, leading to transfers from regular schools to alternative schools due to issues like disruptive behavior, chronic truancy, or academic challenges (NCES, 2002). According to Lehr et al. (2004), alternative schools typically feature smaller class sizes, increased teacher-student interaction, flexible scheduling and structures, and a supportive atmosphere. Some students may be enrolled in alternative schools for a portion of the school year, while others remain in this setting until graduation. Regardless of the duration of enrollment, the unique features of alternative schools can contribute to the success and graduation of students who may be at risk of dropping out.

Similar to traditional schools that serve both general education students and students with disabilities, alternative schools must establish comprehensive policies and procedures and employ qualified personnel capable of addressing the diverse needs of all students. Research indicated that approximately 12% of students in alternative schools have disabilities, mirroring the prevalence of disabilities in regular public schools (Lehr et al., 2004). When students with disabilities transition to alternative schools, their IEP services must continue uninterrupted, and appropriately trained staff members must be available to deliver these services effectively. Despite the importance of this issue, a notable gap remains in national research regarding the services provided to students with disabilities in alternative school settings (Lehr et al., 2004).

Alternative high schools in rural Iowa were the focus of a study conducted by Gilson (2006) to determine the characteristics that effectively promote student graduation. The study examined variables such as teacher and administrator tenure, school size, teacher and student choice, teacher satisfaction, auxiliary services, school autonomy, and learning methodologies. Questionnaires were sent to 70 of the 108 alternative high schools in the state, targeting those with student populations ranging from 26 to 545 students in grades 9 through 11, with at least three years of establishment.

The survey achieved an 87% return rate, revealing that teacher satisfaction emerged as the characteristic most positively impacting student graduation. A significant majority of respondents (81.6%) reported being very satisfied with their decision to teach at an alternative school. Despite an overall graduation rate of 21.6% for the alternative schools reviewed in the study, 79.6% of teachers who reported high job satisfaction indicated that more than half of their students graduated. However, aside from teacher satisfaction, the study found no significant correlations between the variables examined and student graduation rates (Gilson, 2006).

General and Special Education Classrooms. According to a student's IEP, academic support may be provided by a paraprofessional, interpreter, special education teacher, or other special education staff (GaDOE, 2019). When students receive exclusive academic support from special education teachers, it is categorized as a special education classroom, which is considered more restrictive than a general education classroom. Special education classrooms are composed solely of students with disabilities, providing a specialized learning environment tailored to their individual needs.

In the general education classroom setting, students can receive support through various methods. Co-teaching and collaborative teaching involve a partnership in which general and special education teachers jointly instruct students with disabilities in the same classroom, enabling them to access the general curriculum (Friend et al., 2010). With the push to include students with disabilities in general education classrooms as much as possible, co-teaching and collaborative teaching have gained momentum as commonly utilized services. These methods not only facilitate access to the general curriculum for students with disabilities but also promote inclusive practices, provide individualized support, and foster a supportive learning environment that benefits all students.

In their examination of the literature on the academic and social impacts of inclusion for students with disabilities, Kart and Kart (2021) highlighted significant trends. According to their research, data from the U.S. Department of Education in 2020 showed varying inclusion levels across disability categories. For instance, among students with speech impairments, a substantial 85% spent 80% or more of their time in general education classrooms. Similarly, the percentages were notable for students with specific learning disabilities (71.4%) and visual impairments (67.9%). However, the level of inclusion significantly decreased for students with more complex disabilities, with only 13.7% of students with multiple disabilities, 16.9% of students with intellectual disabilities, and 23.6% of students with deafblindness spending 80% or more of their time in general education settings. Nevertheless, studies suggested that increased inclusion in general education settings positively affects the academic and social development of students with disabilities (Kart & Kart, 2021).

Schwartz et al. (2019) investigated the impact of special education services on the academic performance of students with disabilities, focusing specifically on those with LD. Their study analyzed longitudinal data from more than 44,000 students in New York City, tracking their progress from kindergarten through eighth grade over a seven-year period. To assess the effects, they used within-student pre/post comparisons and student-fixed-effects regression models. They found that special education services have statistically significant effects on students with disabilities in math and ELA, with effect sizes of 0.116 and 0.055, respectively. Additionally, they discovered that nearly two-thirds of students with LD are placed in special education teacher support services, where they can receive either in-class support or be pulled out for individual services. In contrast, 28% of students receive integrated co-teaching services. Schwartz et al. (2019) noted that students identified in grades four and five were placed in less restrictive environments compared to those identified in later grade levels.

Alternatively, students may receive consultative services, which entail periodic consultations between the student and a special education teacher throughout the school year, typically totaling 60 minutes per month. Consultative services aim to provide targeted support and guidance to both the student and the general education teacher, facilitating the implementation of accommodations and modifications in the classroom (GaDOE, 2019). Additionally, support in the general education classroom can be facilitated by including paraprofessionals, interpreters, or other special education staff members who assist students as needed. Paraprofessionals, for example, may provide direct support to students with disabilities, including academic assistance, behavior management, and facilitating access to instructional materials. Interpreters play a crucial role in facilitating communication for students with hearing impairments, ensuring they can fully participate in classroom activities. Other special education staff members may provide specialized interventions or supplementary aids to support students in achieving their academic goals (GaDOE, 2019).

Separate Special Education School. In instances where special education services within a traditional school setting are inadequate to meet the needs of students with severe disabilities, separate special education schools exist, comprising solely of special education classrooms (GaDOE, 2019). These schools represent the most restrictive educational setting for students with disabilities, as they do not receive education outside of the special education environment. However, this level of restriction is intended to ensure that students with complex needs receive the specialized support and resources necessary to meet their unique learning needs.

Research on the outcomes of restrictive placement on student graduation rates yields mixed results, as noted by Foreman-Murray et al. (2022). In their literature review, Foreman-Murray et al. (2022) identified four studies indicating a negative correlation between the restrictive placement of students with EBD and their attainment of a regular high school diploma. Furthermore, despite a broader trend toward inclusion for students with disabilities, those with EBD are disproportionately placed in restrictive environments compared to students with other disabilities. Overall, Foreman-Murray et al. (2022) suggested a lower dropout rate for students with EBD in the most restrictive environments; however, these students are more likely to graduate with an alternative diploma rather than a regular diploma.

In Georgia, the Georgia Network for Educational and Therapeutic Support (GNETS) program is one of the most widely utilized special education programs, specifically designed to serve students with disabilities in separate school settings (Hinton & McGuire, 2010). A performance audit published in 2010 revealed concerning statistics: only 10% of students enrolled in the GNETS program in the 2004-2005 school year graduated with a regular diploma, while a staggering 40% were classified as dropouts. Given the significant funding allocated to the GNETS program, totaling $64 million in 2010, state authorities recognized the imperative for enhanced tracking and accountability measures to improve outcomes for the most vulnerable students (Hinton & McGuire, 2010).

Predictive Modeling and Machine Learning Approaches

In addition to research on student-level and school-level factors, scholars have increasingly examined the use of predictive modeling techniques to identify students at risk of dropping out. Márquez-Vera et al. (2016) found that while machine learning methods such as support vector machine and neural network sometimes offer modest gains in predictive sensitivity, these improvements often require large datasets, extensive parameter tuning, and considerable technical expertise to outperform traditional models.

Likewise, Aulck et al. (2017) reported that although random forests and neural networks occasionally surpassed logistic regression in predicting college persistence, the performance gap was typically small unless researchers used very large or longitudinal datasets. Taken together, these studies suggested that for moderate sample sizes and binary outcomes such as graduation versus non-graduation, logistic regression remains a practical and effective modeling choice.

Summary

This literature review highlighted the significance of high school graduation and the potential consequences of dropping out. Discussed methods for calculating graduation and dropout rates, along with the historical context of these calculations, established a foundation for the variables used in the current study. The student-level factors examined included disability classification, English proficiency (EL status), gender, race and ethnicity, socioeconomic status, failed classes, grade retention, student attendance, and behavior referral. The school-level factors, specifically those affecting students with disabilities, included IEP services such as collaborative instruction, consultative service, co-teaching instruction, direct instruction, and supportive services, as well as the various learning environments these students may experience.

Additionally, recent research has employed predictive modeling approaches to understand and forecast the risk of student dropout. Studies using both traditional statistical methods and machine learning techniques have explored how academic, behavioral, and demographic factors interact to predict graduation outcomes. Collectively, these studies showed that while complex machine learning models can offer modest improvements under certain conditions, logistic regression often provides a practical and effective approach for moderate sample sizes and binary outcomes such as graduation status versus non-graduation. Taken together, the literature reviewed substantiates the need for further research on students with disabilities, focusing on the specific factors that influence graduation outcomes while also leveraging appropriate predictive modeling techniques to inform early interventions and policy decisions for this group.

Chapter III

Methodology

This chapter presents the research methods employed in this non-experimental correlational study, utilizing historical data from a rural school district in South Georgia. Adopting selected elements of the framework proposed by Hammond et al. (2007), the current study identified student-level and school-level factors that may contribute to a student's decision to graduate from high school, as well as the classification model that is most accurate in identifying these factors. This chapter is divided into five sections, beginning with the research design, which includes the independent and dependent variables. The second section focused on the population and participants of the current study. The third section describes the data collection process and discusses the data's accuracy and reliability. The fourth section outlines the data analysis procedures used for each research question. The final section summarizes the chapter.

The research questions framing the current study were:

1. Are any student-level or school-level factors significant predictors of high school graduation status for students with disabilities?

2. Which of the data mining models (binomial logistic regression, neural network, random forest, and support vector machine) can generate a more accurate prediction of high school graduation status based on the evaluation metrics of accuracy, precision, recall, and F1 score?

Research Design

The current study adopted a non-experimental, correlational research design to explore the relationship between various variables and graduation outcomes among students with disabilities. Correlational studies aim to identify associations between two or more variables (Creswell & Creswell, 2018), making them well-suited for investigating the complex interplay of factors that influence student outcomes.

The research design consisted of two main components, aligned with the research questions. The first research question in the current study followed Dynarski et al.'s (2008) recommendation that preventing dropout for at-risk students should begin with identifying student-level and school-level problems before implementing interventions. To address this question, the study employed binomial logistic regression to model the probability of graduating based on the predictor variables. These include student-level factors—such as demographics (disability classification, English proficiency, gender, race and ethnicity, and socioeconomic status), academic performance (failed classes and grade retention), and non-academic performance (student attendance and behavior referrals)—as well as school-level factors, including IEP services and learning environments. Binomial logistic regression was selected as the statistical technique due to its suitability for analyzing the binary outcome variable of graduation status and its ability to handle a wide range of predictor variables, as in the current study.

To address the second research question, four data mining models (binomial logistic regression, neural network, random forest, and support vector machine) were implemented on the same dataset to compare their performance to determine which one(s) produced the most accurate results. The models were compared using the evaluation metrics of accuracy, precision, recall, and F1 scores. This comparative analysis identified the most effective predictive model for understanding graduation outcomes among students with disabilities.

Population and Participants

The current study utilized student data from a mid-sized rural school district in South Georgia. The selection of this district was based on several factors. First, the researcher's professional affiliation with the district allowed for access to relevant data. It increased the likelihood that the study's findings would inform positive, data-driven improvements within the district. Second, privacy concerns limited the feasibility of including additional districts, as accessing comparable data would require the use of PII, such as GTIDs. Finally, the sample size available from this district was sufficient to conduct the proposed statistical analyses and provides a meaningful basis for examining the relationship between student-level and school-level factors and high school graduation outcomes for students with disabilities.

As a rural district, many components of rural education may arise at the district level (e.g., a geographically dispersed population, long travel distances, and limited access to behavioral and mental health services). Such characteristics guide how supports are provided to students and the design of intervention programs. Further details on the rural context are provided in the next section.

According to data from the Governor's Office of Student Achievement website (GOSA, n.d.), the school district supported 14,359 students in the 2022-2023 school year. This student population was composed of 65% White, 17% Black, 11% Hispanic, 6% multiracial, and 1% Asian students. Additionally, 39% of these students were eligible for free or reduced lunch, 15.4% were students with disabilities, and 3% were English

Learners. The district contained two high schools, three middle schools, eight elementary schools, an alternative school, a separate special education school, and a College and Career Academy.

The current study included all students with disabilities who entered ninth grade in 2018, 2019, and 2020 in the selected district in South Georgia. These students were expected to graduate in 2022, 2023, and 2024. For these cohorts, student data were excluded if the student transferred into the district less than two years prior to their expected graduation date, regardless of their graduation status at the time of transfer. Students who transferred out before graduation or who passed away were also excluded from the analysis. Only students who successfully completed high school with a high school diploma were considered graduates; any other diploma or certificate was considered a dropout.

Rural Education Setting

The participating school district is situated in a rural region of South Georgia. Although the area remains geographically rural, with large tracts of land, agricultural activity, and small-town forms of community, it has experienced rapid population growth over the past decade. This expansion has resulted in increased student enrollment, new housing development, and a growing need for educational facilities. Despite these demographic changes, many rural characteristics persist, including long travel distances for some students, dispersed residential communities, and limited local access to specialized external services.

Unlike many rural districts that struggle to hire and retain qualified teachers, this district has maintained a strong reputation as a desirable place to work. Stable leadership, strong community engagement, and competitive employment conditions have contributed to a consistent and highly qualified workforce. As a result, the district has not experienced the staffing shortages or high turnover rates commonly described in rural education research. This level of stability may positively influence school climate, instructional quality, and the consistent implementation of supports for students with disabilities.

The district also reflects several features typical of rural educational settings. Students may spend considerable amounts of time on school buses, which can affect participation in before- and after-school programs, extracurricular activities, and intervention services. Additionally, the surrounding community has limited availability of external behavioral health, mental health, and specialized academic service providers. These constraints increase the responsibility of the school system to provide comprehensive support for students, including those with disabilities.

The district serves a socioeconomically diverse population, including both middle-income and economically disadvantaged households, and several schools qualify for Title 1 funding. In rural areas, economic hardship may be compounded by limited access to community agencies, transportation challenges, and reduced availability of healthcare and social services. These factors coincide with the needs of students with disabilities and influence the types and intensity of interventions schools must provide. At the same time, strong community cohesion and close relationships between families and school personnel, often found in rural communities, may contribute to positive student engagement and improved academic outcomes.

Overall, the rural context of this district provides an important backdrop for interpreting graduation outcomes for students with disabilities. Geographic rurality, rapid population growth, stable staffing, and strong community-school relationships combine to create a unique educational environment. Understanding how these contextual factors influence student outcomes offers valuable insight into the broader literature on rural education and the experiences of students with disabilities.

Instrumentation

The current study utilized data collected by the district and submitted to the GaDOE for the required annual data collections from 2022 to 2024, as well as the files provided by the GaDOE for the district's CCRPI calculations. Each year, school districts in Georgia are required to submit data in October and March for the Full-Time Equivalent (FTE) and Student Class data collections, and in June for the collections of Student Class Files and Student Record Files (GaDOE, n.d.-b; Georgia Insights, n.d.).

Student Class Files included data on the students' schedules, rosters, teacher information, and details about the services provided to students in their classes for special education, gifted programs, remedial education, and English Learner programs. Additionally, these files included students' scores in their classes.

Student Record Files consisted of multiple file types, including:

- Address Level Files: Information on student addresses.
- Enrollment Level Files: Details on student enrollment in the district.
- Program Level Files: Information on the educational program students are enrolled in.
- School Level Files: Data specific to the schools within the district.

- Special Education Level Files: Information on special education services and settings provided.
- Student Level Files: General student information.
- Student Safety Files: Data related to behavior incidents.
- System Level Files: General information on the school district as a whole.

The data collected through these annual reports were used to generate the College and Career Ready Performance Index (CCRPI) reports. The CCRPI reports provided metrics that measure schools' performance in preparing students for college and career readiness, based on academic achievement, progress, closing gaps, readiness indicators, and graduation rates. Along with the CCRPI reports, the GaDOE provided districts with the detailed files used for calculations. The information in these files, in addition to the data collection files, encompassed all aspects related to the school system and students for the entire year (GaDOE, n.d.-b; Georgia Insights, n.d.).

Reliability and Validity

Reliability

The reliability of the data collection instruments — Student Class files, Student Record files, and CCRPI reports — was supported by their systematic and repetitive use over a span of six years, from 2018 to 2024. Districts adhered to a consistent schedule for submitting data in October, March, and June each year, ensuring a reliable, continuous flow of information. Multiple stages of verification and quality checks, conducted by both district administrators and the GaDOE, further enhanced accuracy by minimizing potential errors.

The use of electronic student information systems standardized the collection, storage, and processing of data, reducing variability due to human error and ensuring uniformity across all districts. Additionally, the longitudinal nature of the dataset provided a valuable basis for identifying trends and patterns in student outcomes over time, reinforcing the reliability of the data collection process. This consistency, coupled with stringent quality control measures, ensured that the data are dependable for analysis and interpretation.

Validity

The validity of the data collection instruments — Student Class files, Student Record files, and CCRPI reports — was reinforced by their alignment with state and federal educational reporting requirements. These instruments were specifically designed to capture comprehensive data on student enrollment, educational services, class schedules, disability classifications, and performance outcomes, which were central to the study's objectives of examining factors affecting the graduation status of students with disabilities.

The Student Class and Student Record data collections gathered detailed information that supported the construct validity of the study by focusing on relevant factors such as participation in special education services, attendance, and academic achievement. Additionally, the comprehensive nature of these datasets ensured high content validity, as they encompassed a wide range of variables critical to understanding educational outcomes for students with disabilities.

Using standardized data submission protocols across districts further strengthened the study's internal validity by reducing measurement bias and ensuring consistent data collection. This uniformity enabled meaningful comparisons across different districts and schools over time, thereby enhancing the overall validity of the study's findings. While the generalizability of the findings was somewhat limited to districts in Georgia, the standardized nature of the data collection process ensured that the findings could be applied more broadly to similar educational contexts.

Variables

Independent Variables

The study examined 11 factors categorized into two main groups—student-level and school-level factors—identified as the independent variables. These variables were selected based on a comprehensive literature review of potential predictors of dropout. Student-level factors included demographics (disability classification, English proficiency - EL status, gender, race and ethnicity and socioeconomic status - free/reduced meal status), academic performance (failed classes and grade retention), and non-academic performance (attendance - missing more than 10% of enrolled days and behavior referrals) (Bear et al., 2006; Blazer & Gonzalez Hernandez, 2018; McDermott et al., 2019; Rumberger, 2011; Rumberger & Lim, 2008; Wagner et al., 2006; Wood et al., 2017; Zablocki & Krezmien, 2013).

Within the student-level factors group, there were seven nominal variables and two ordinal variables. The nominal variables included disability classification, EL status, gender, race and ethnicity, socioeconomic status, attendance, and grade retention. The disability categories included Emotional and Behavioral Disorder, Blind, Intellectual Disability, Autism, Other Health Impairment, Specific Learning Disability, Speech-Language Impairment, Traumatic Brain Injury, and Visual Impairment. Dummy variables were generated for categorical variables with more than two levels to allow them to be included in the regression model. EL status was coded as 1 for EL students and 0 for non-EL students. Gender was coded with 1 for males and 0 for females. The race and ethnicity variable was represented by six levels: Black, Hispanic, Asian, American Indian or Alaska Native, White, and Other/Unknown/Multiple. Dummy variables were generated for categorical variables with more than two levels to allow them to be included in the regression model. Socioeconomic status was coded as 1 for students who qualify for free/reduced lunch and 0 for those who do not qualify (GaDOE, n.d.-b). Attendance was coded based on the percentage of missed days. Students who missed more than 10% of their enrolled days were coded as 0, while those who did not miss more than 10% were coded as 1. Grade retention was coded as 1 for students who were retained at least once during high school and 0 for those who were not.

The ordinal variables were behavior referrals and failed classes. Behavior was categorized into three groups: zero referrals, one to three referrals, and more than three referrals as categorical groups. Failed classes were categorized into three groups: zero failed classes, one failed class, and more than one failed class. Dummy variables were generated for categorical variables with more than two levels to allow them to be included in the regression model.

Within the school-level factors group, there were two nominal variables: IEP services and learning environments. Since students could receive multiple IEP services, each service was coded as a separate dichotomous variable. Specifically, five binary variables were created for collaborative instruction, consultative service, co-teaching instruction, direct instruction, and supportive service, where 1 indicated that the student received the service and 0 indicated that they did not. This approach allowed for the possibility that a student may receive multiple services simultaneously.

Similarly, since students may experience multiple learning environments throughout their education, each environment was also coded as a separate dichotomous variable. Four binary variables were created for alternative school, general education classroom, special education classroom, and separate special education school, as 1 indicating that the student spent time in that environment and 0 indicating they did not. This method enabled the study to capture students' exposure to multiple learning settings rather than assuming a single placement. These variables were included based on recommendations from previous research conducted by Friend et al. (2010), Gilson (2006), Kurth et al. (2019), and Lehr et al. (2004).

Dependent Variable

The dependent variable in the current study was graduation status, defined as whether a student graduated from high school within four years. This status pertained specifically to earning a regular high school diploma and excluded special education diplomas or other alternative diplomas. Graduation status was a nominal variable, with 1 indicating graduation and 0 indicating non-graduation.

Each variable was informed by relevant research, ensuring a comprehensive examination of factors that may influence graduation status among students with disabilities. By examining the relationship between these independent and dependent variables, the study aimed to uncover key factors associated with graduation outcomes. Understanding these relationships was crucial for identifying potential risk factors and informing targeted interventions to support students at risk. By delineating these associations, educators and policymakers could develop strategies to address barriers to academic success and promote equitable educational outcomes for all students, including those with disabilities.

Data Collection

Once the Valdosta State University Institutional Review Board (IRB) granted permission to collect research data (see Appendix A), data were obtained from the district-level administrators of student information in the district (see Appendix B). Student information was housed within their specific student information system, which was Infinite Campus. To maintain consistency across year cohorts, the data collected for the current study included the Student Class and Student Record files that the districts transmitted to the GaDOE for the annual data collection, as well as the CCRPI files received from the GaDOE each year. Students were cross-matched in these files using a unique identifier, and a randomly generated number was assigned to ensure data anonymity. The data were stored in a password-protected file to ensure security and confidentiality. Only my guiding professor and I had access to the dataset. In compliance with VSU institutional guidelines, the data will be deleted three years after the completion of the research.

Data Analysis

Data analysis for the current study consisted of two distinct components that aligned with the research questions. After preprocessing the data to handle missing values, encoding categorical variables, and standardizing numerical variables, the dataset was split into training and testing sets to validate the model's performance (Kuhn & Johnson, 2013). For research question one, descriptive statistics were reported for the individual variables. This included frequency distributions, measures of central tendency, and measures of dispersion to provide an overview of the data and examine the relationships between the independent and dependent variables (Creswell & Creswell, 2018). To determine which factors were significant predictors of high school graduation among students with disabilities, a binomial logistic regression model was fit to the data. This model assessed the extent to which student-level and school-level factors predict the likelihood of graduation. The significance of each predictor variable was evaluated using the model's coefficients and *p*-values, while odds ratios were utilized to understand the strength and direction of the associations (Kuhn & Johnson, 2013).

For research question two, four different models — binomial logistic regression, neural network, random forest, and support vector machine — were trained on the training dataset. After training and testing each model, their predictive performance was compared using evaluation metrics such as accuracy, precision, recall, and F1 score to determine which model generates the most accurate student outcome predictions (Owusu-Adjei et al., 2023).

Summary

This chapter presents the design and methodology used in this non-experimental, correlational study to identify factors influencing the graduation status of students with disabilities. The independent variables (disability classification, English proficiency - EL status, gender, race and ethnicity, socioeconomic status, failed classes, grade retention, attendance, behavior referrals, IEP services, and learning environments) for the current study were selected based on a thorough literature review of student-level and school-level factors affecting students' graduation status with regards to students with disabilities.

The current study included all students with disabilities who entered the ninth grade in 2018, 2019, and 2020 in a rural school district in Georgia. The dataset was split into training and test data to evaluate different statistical models and determine which is most accurate at predicting the eventual graduation status of students with disabilities. The study's analysis was conducted using SPSS software.

The first research question in the current study aimed to determine the significance of 11 factors at both the student and school levels on the graduation status of students with disabilities. The independent variables included nine student-level factors (disability classification, English proficiency - EL status, gender, race and ethnicity, socioeconomic status, failed classes, grade retention, attendance, and behavior referrals), as well as two school-level factors (IEP services and learning environments). Binomial logistic regression was used to analyze these variables and their impact on student graduation status. For the second research question, four data mining models (binomial logistic regression, neural network, random forest, and support vector machine) were employed and evaluated to determine the model that best predicts the eventual graduation status of a student with disabilities.

Chapter IV

Results

The purpose of this non-experimental, correlational study was to utilize historical data from three graduation cohorts in a South Georgia school district to provide teachers and administrators with insights into potential factors influencing the graduation outcomes of students with disabilities (SWD). The analytic sample comprised SWD enrolled in a mid-sized rural public school district in South Georgia. According to district records for the 2022–2023 school year, the system served 14,359 students across two high schools, three middle schools, eight elementary schools, an alternative school, a separate special education school, and a college and career academy. Approximately 15.4% of students were identified as having disabilities. Students were eligible for inclusion if they first entered Grade 9 in 2018, 2019, or 2020, corresponding to four-year graduation cohorts expected to complete in 2022, 2023, and 2024. Based on pre-analysis counts, the anticipated SWD sample size across these cohorts was $N = 673$ (2018–2022: $n = 240$; 2019–2023: $n = 250$; 2020–2024: $n = 183$). Records were excluded if students transferred into the district fewer than two years before their expected graduation date, transferred out prior to graduation, or died during the observation window. After excluding cases that did not meet the required criteria, 425 valid cases remained for the final analysis.

The research questions framing the current study were:

1. Are any student-level or school-level factors significant predictors of high school graduation status for students with disabilities?

2. Which of the data mining models (binomial logistic regression, neural network, random forest, and support vector machine) can generate a more accurate prediction of high school graduation status based on the evaluation metrics of accuracy, precision, recall, and F1 score?

The outcome variable, graduation status, was coded as receipt of a regular high school diploma within four years (graduated) versus all other outcomes (non-graduated); alternative diplomas or certificates were categorized with the non-graduation group. Predictor variables represented student-level factors (e.g., disability classification, English proficiency, gender, race and ethnicity, socioeconomic status, failed courses, grade retention, attendance, and behavior referrals) and school-level factors (IEP services and learning environments). Data were drawn from routinely collected administrative files (e.g., Student Class, Student Record, and CCRPI files). They were de-identified prior to analysis in accordance with district and university requirements.

The remainder of this chapter presents the data analysis process, including the results for each research question. First, this chapter focuses on the descriptive characteristics of the sample, followed by a summary of the instrumentation and data preparation procedures. Subsequent sections presented statistical results addressing the research question. First, findings from the binomial logistic regression analysis were reported. Next, the predictive accuracy of the logistic regression, neural network, random forest, and support vector machine models was compared across evaluation metrics.

Finally, the chapter concludes with a summary of findings and a transition into Chapter V.

Data Preparation and Variable Coding

Data preparation followed a reproducible SPSS workflow consistent with the methodology. First, empty imports were removed using a selection rule keyed to the de-identified random number field (*select if not missing(RandomNumber)*). Next, string indicators were converted to numeric format as follows: values of "Y" and "N" in *Retained* were recoded to 1 and 0, respectively, and year-specific attendance strings marked "NA" were blanked prior to type conversion (*alter type* to F1). Value labels were applied to all categorical variables to ensure clarity in output and alignment with reporting conventions.

Dummy variables are used in logistic regression because the model can only work with numerical values, not categorical ones. By converting each category into a 0/1 variable, the model can accurately compare each group to a chosen reference group and estimate the impact of each category on the outcome. Dummy variables were created for categorical variables with more than two levels to allow inclusion in the regression model, including Disability Classification, Race and Ethnicity, Failed Classes, and Behavior Referrals. The variable coding is listed below. After recoding, frequencies and crosstabs were inspected to confirm that marginal totals matched the demographic tallies reported above and that no out-of-range values remained.

Dependent Variable

The dependent variable, *Graduation Status*, was coded as 1 for receipt of a regular high school diploma within four years and 0 for all other outcomes (e.g., alternative diplomas, certificates, or noncompletion).

Independent Variables

Student-Level Variables. The following student-level variables were included:

Demographics:

- *Disability Classification.* Disabilities were collapsed to six levels, including autism, intellectual disability, emotional/behavioral disorder, specific learning disability, other health impairment, and combining sensory categories (e.g., blindness, speech-language impairment, traumatic brain injury, deaf-blindness into "sensory/communication disability.

  1 = sensory/communication disability,

  2 = autism,

  3 = intellectual disability,

  4 = emotional/behavioral disorder,

  5 = specific learning disability,

  6 = other health impairment.
- *ELStatus* (1 = English Learner, 0 = non-EL)
- *Gender* (1 = male, 0 = female)
- *Race and Ethnicity*. Race was collapsed to four levels, including Black, Hispanic, and combining Asian and American Indian or Alaska Native with "other / unknown / multiple.

1 = Black

2 = Hispanic

3 = White

4 = Other/Unknown/Multiple

- *Socioeconomic Status* (1 = qualified for free/reduced-price lunch, 0 = did not qualify)

Academic Performance:

- *Failed Classes* (0 = none, 1 = one course, 2 = > 1 course)
- *Grade Retention* (1 = retained at least once, 0 = not retained)

Non-Academic Performance:

- *Attendance* was coded as a binary indicator: 0 = missed > 10% of enrolled days in any observed year, 1 = ≤ 10% of enrolled days in all observed years.
- *Behavior Referrals* (0 = none, 1 = 1–3, 2 = > 3)

School-Level Variables. The following school-level variables were included:

- **IEP Services**. Indicators of IEP services were coded as five dichotomous variables: collaborative instruction, consultative service, co-teaching instruction, direct instruction, and supportive service (1 = received at least once during high school, 0 = never received).
- **Learning Environments**. Learning environments were coded as four dichotomous variables: alternative school, general education classroom, special education classroom, and separate special education school (1 = placed in that setting at any time, 0 = not placed).

Missing Data

A univariate review indicated complete data for all predictors except attendance (chronic absence). Among the 425 records, the following indicators had 0% missing values: *Disability Classification, EL Status, Gender, Race and Ethnicity, Socioeconomic Status, Failed Classes, Grade Retention, Behavior Referrals, Graduation Status, and all IEP service and learning environment indicators* (see Table 2). The *Attendance* variable had 112 missing cases (26.4%), leaving 313 complete observations for that field. The missing-pattern table showed only one pattern: either a record was complete on all variables (n = 313), or it was missing only *Attendance* (n = 112). No multivariable missing clusters were observed.

Data were checked for legal values and internal consistency. All IEP service and learning environment indicators were verified as 0/1 dichotomies, with simultaneous 1s permitted within each set (consistent with students receiving multiple services and placements). Category codes for multi-level variables (e.g., *Disability Classification*, *Race and Ethnicity*, *Failed Classes*, and *Behavior Referrals*) aligned with the study codebook, and no out-of-range or illogical combinations were identified.

Missing data were reported using valid percentages. For attendance, percentages were based on the 313 non-missing cases, and the proportion of missing values was noted. Attendance had 26.4% missing because some students lacked year-level attendance files across all four years. This variable was derived as a binary summary from multiple year-level flags (2018, 2019, 2023, and 2024); cases with no year available were assigned a missing value. The cause of the missing data was not random "noise", but was tied to the cohort of which the student belonged. Therefore, complete-case analysis would have removed 26.4% of the sample. This was treated as missing-at-random (MAR), conditional on observed covariates and cohort.

Table 2

Univariate Missing Data by Variable (N = 425)

Variable	*n*	Missing (*n*)	Missing (%)
Demographics -			
Disability Classification	425	0	0
EL Status	425	0	0
Gender	425	0	0
Race and Ethnicity	425	0	0
Socioeconomic Status	425	0	0
Academic Performance -			
Failed Classes	425	0	0
Grade Retention	425	0	0
Non-Academic Performance -			
Attendance	313	112	26.4
Behavior Referrals	425	0	0
Graduation Status -	425	0	0
IEP Services -			
Collaborative Instruction	425	0	0
Consultative Service	425	0	0
Co-teaching Instruction	425	0	0
Direct Instruction	425	0	0
Supportive Service	425	0	0
Learning Environments -			
Alternative School	425	0	0
General Education Classroom	425	0	0
Special Education Classroom	425	0	0
Separate Special Education School	425	0	0

For Research Question 1, missing attendance values were imputed using fully conditional specification (FCS) with a logistic model to impute the binary attendance indicator (0 = > 10% missed; 1 = ≤ 10%). The imputation model included all analysis variables (*Disability Classification, EL Status, Gender, Race and Ethnicity,* *Socioeconomic Status, Failed Classes, Grade Retention, Behavior Referrals, Collaborative Instruction, Consultative Service, CoTeaching Instruction, Direct Instruction, Supportive Service, Alternative School, General Education Classroom, Special Education Classroom, and Separate Special Education School*), the outcome (*Graduation Status*), cohort, and an indicator of whether any year-level *Attendance* was observed. Five imputations were generated, and logistic regressions were fitted separately within each dataset, with parameter estimates and 95% confidence intervals pooled using Rubin's rules.

For Research Question 2, the four classifiers (binomial logistic regression, neural network, random forest, and support vector machine) were trained on an imputed dataset to account for missing values. To test the robustness of the findings, models were also evaluated using a three-level Attendance encoding: 0 indicated poor attendance, 1 indicated good attendance, and 2 represented missing or unknown attendance data. The results were consistent across both specifications, indicating the models' predictive performance is stable.

Analysis Platform, Imputation, and Procedures

All analyses were conducted in IBM SPSS Statistics. The only variable with missing data was the binary attendance indicator (0 = chronically absent in any year [≥ 10%]; 1 = not chronically absent in all observed years). For Research Question 1, missing *Attendance* values were handled using multiple imputation with FCS and a logistic model appropriate for binary outcomes. Five imputations were generated, and binomial logistic regression models were estimated separately within each completed dataset. The resulting coefficients, standard errors, and 95% confidence intervals were then pooled using

Rubin's rules. All other predictors and the dependent variable were fully observable and were analyzed accordingly.

For Research Question 2, all predictive models were trained on the imputed dataset using a single 70/30 stratified train-test split generated once with a fixed random seed for consistency. Logistic regression and multilayer perceptron (MLP) neural networks were fitted using SPSS's built-in procedures, while the random forest and support vector machine (SVM) models with a radial basis function (RBF) kernel were implemented via IBM extension commands. For each model, predicted class membership and probabilities were saved, and performance metrics, including accuracy, precision, recall, and F1 scores, were calculated from a shared SPSS syntax block to ensure uniform evaluation across classifiers.

Descriptive Statistics

Student-Level Factors

Demographics. The demographics of the analytic sample (N = 425 valid cases) were summarized in Table 3. The majority of students (99.1%, n = 421) were classified as non-EL, with only 0.9% (n = 4) identified as EL. Males comprised 65.6% (n = 279) of the sample, while females accounted for 34.4% (n = 146). Regarding socioeconomic status, 41.4% (n = 176) of students qualified for free or reduced-price lunch, while 58.6% (n = 249) did not.

The most common primary disability classifications were other health impairment (OHI; 41.6%, n = 177) and specific learning disability (SLD; 28.9%, n = 123). Smaller proportions were identified with autism (11.1%, n = 47), intellectual disability (9.4%, n = 40), emotional and behavioral disorder (7.5%, n = 32), and sensory/communication disability (1.4%, n = 6). For race and ethnicity, 63.3% (n = 269) were White, 22.6% (n = 96) were Black, 8.9% (n = 38) were Hispanic, and 5.2% (n = 22) were another race, unknown, or multiple races. The racial composition of the sample indicated that 63.3% of students identified as White.

Table 3

Demographics (N = 425)

Category | Level	*n*	%
Disability Classification -		
Sensory/Communication Disability	6	1.4
Autism	47	11.1
Intellectual Disability	40	9.4
Emotional and Behavioral Disorder	32	7.5
Specific Learning Disability (SLD)	123	28.9
Other Health Impairment (OHI)	177	41.6
English Learner (EL) Status -		
Non-EL students	421	99.1
EL students	4	0.9
Gender -		
Females	146	34.4
Males	279	65.6
Race and Ethnicity -		
Black	96	22.6
Hispanic	38	8.9
White	269	63.3
Other/Unknown/Multiple	22	5.2
Socioeconomic Status -		
Not qualify for free/reduced-price lunch	249	58.6
Qualify for free/reduced-price lunch	176	41.4

Note. Abbreviations: EL = English Learner; SLD = Specific Learning Disability; OHI = Other Health Impairment.

Academic and Non-Academic Performance. Descriptive statistics for the study's academic and non-academic performance variables were summarized in Table 4. Nearly two in five students (39.3%, n = 167) failed more than one class, 13.6% (n = 58) failed exactly one class, and 47.1% (n = 200) did not fail any classes. Grade Retention was common: 46.8% (n = 199) were retained at least once, and 53.2% (n = 226) were not retained. Attendance was summarized as chronic absence; among cases with observed attendance data (valid n = 313), 30.0% (n = 94) missed more than 10% of enrolled days in at least one year, and 70.0% (n = 219) did not. Most students had no behavior referrals (67.8%, n = 288), whereas 15.8% (n = 67) had 1–3 referrals and 16.5% (n = 70) had more than three.

Table 4

Descriptive Statistics for Key Variables (N = 425)

Variable | Level	n	%
Failed Classes -		
0	200	47.1
1	58	13.6
> 1	167	39.3
Grade Retention -		
Not retained Students	226	53.2
Retained Students	199	46.8
Attendance -		
Missed more than 10% of enrolled days	94	30.0
Did not miss more than 10%	219	70.0
Behavior Referrals -		
0	288	67.8
1 – 3	67	15.8
> 3	70	16.5
Graduation Status -		
Did not Graduate	102	24.0
Graduated	323	76.0

Table 4 (continued).

Variable | Level	n	%
IEP Services -		
Collaborative Instruction		
Did not receive	425	100.0
Received	0	0.0
Consultative Service		
Did not receive	363	85.4
Received	62	14.6
Co-Teaching Instruction		
Did not receive	130	30.6
Received	295	69.4
Direct Instruction		
Did not receive	131	30.8
Received	294	69.2
Supportive Service		
Did not receive	127	29.9
Received	298	70.1
Learning Environments -		
Alternative School		
Did not spend time	355	83.5
Spent time	70	16.5
General Education Classroom		
Did not spend time	61	14.4
Spent time	364	85.6
Special Education Classroom		
Did not spend time	199	46.8
Spent time	226	53.2
Separate Special Education School		
Did not spend time	406	95.5
Spent time	19	4.5

Note. Percentages are valid percentages within each variable and may not sum to 100 due to rounding. *Attendance* percentages are based on valid cases (n = 313; 112 cases missing).

School-Level Factors

Consistent with the analysis plan, IEP services and learning environments were recorded as separate binary indicators and were not mutually exclusive. No students received collaborative instruction during the observation window (0.0%, $n = 0$). Consultative services were recorded for 14.6% ($n = 62$). Co-teaching and direct instructions were common (69.4%, $n = 295$; and 69.2%, $n = 294$, respectively), and supportive services were recorded for 70.1% ($n = 298$). Because collaborative instruction exhibited no variance (i.e., 0% received), it was treated as a constant and was omitted from the inferential models to avoid estimation issues. Regarding learning environments, 16.5% ($n = 70$) spent time in an alternative school, 85.6% ($n = 364$) in a general education classroom, 53.2% ($n = 226$) in a special education classroom, and 4.5% ($n = 19$) in a separate special education school.

Statistical Considerations and Assumptions

The dependent variable, *Graduation Status*, was binary (0 = did not graduate, 1 = graduated); 76.0% ($n = 323$) graduated, and 24.0% ($n = 102$) did not (see Table 4). Each record represented a unique student, and no clustering was modeled at the school level. Therefore, the assumption of independence of observations was satisfied by the study design. Because all independent variables (predictors) were categorical, the linearity-in-the-logit assumption for continuous predictors was not applicable.

Multicollinearity was evaluated using variance inflation factors (VIFs) estimated in SPSS with the regression procedure. As shown in Table 5, VIFs ranged from 1.044 to 2.077 (minimum tolerance = 0.481), well below common thresholds for concern (e.g., 5.0). The highest values were observed for co-teaching instruction (VIF = 2.077), special education classroom (VIF = 1.811), general education classroom (VIF = 1.712), and direct instruction (VIF = 1.545); all remaining predictors had values between 1.00 and 1.40. The collaborative instruction variable exhibited no variance in the analysis files and was automatically omitted. Overall, these results indicated minimal multicollinearity, although moderate overlap among some IEP service and learning environment variables may have modestly inflated standard errors.

Table 5

Variance Inflation Factors (VIF) for Logistic Regression Predictors

Predictors	Tolerance	VIF
Demographics -		
Disability	0.810	1.235
EL Status	0.953	1.050
Gender	0.920	1.088
Race and Ethnicity	0.958	1.044
Socioeconomic Status	0.895	1.117
Academic Performance -		
Failed Classes	0.782	1.279
Grade Retention	0.837	1.195
Non-Academic Performance -		
Attendance	0.865	1.156
Behavior Referrals	0.741	1.349
IEP Services -		
Consultative Service	0.855	1.169
Co-Teaching Instruction	0.481	2.077
Direct Instruction	0.647	1.545
Supportive Service	0.713	1.403
Learning environments -		
Alternative School	0.793	1.261
General Education Classroom	0.584	1.712
Special Education Classroom	0.552	1.811
Separate Special Education School	0.773	1.294

Note. All VIFs < 2.078, indicating minimal multicollinearity.

Sample size adequacy was assessed using the events-per-parameter (EPP) heuristic. With $N = 425$, 323 events (graduates), and approximately 25 model parameters after one-hot/dummy coding (five contrasts for disability; EL status; gender; three contrasts for race and ethnicity; socioeconomic sstatus; two contrasts for failed classes; grade retention; attendance; two contrasts for behavior referrals; four IEP service indicators, consultative service, co-teaching instruction, direct instruction, supportive service; and four learning environment indicators, alternative school, general education classroom, special education classroom, separate special education school), the EPP was ≈ 12.9 (323/25). This exceeded the commonly recommended minimum of 10 (Dhiman et al., 2023). However, the number of non-events was 102, which, together with several sparse categories, for example, EL Status = 1 ($n = 4$), separate special education school ($n = 19$), and IEP consultative service ($n = 62$), suggested that some coefficients might be estimated with reduced precision and wider confidence intervals. IEP collaborative instruction exhibited no variance (0% received) and was excluded from all modeling procedures.

Frequency checks confirmed adequate support for most predictors (e.g., co-teaching instruction = 295, direct instruction = 294, supportive service = 298; alternative school = 70; general education classroom = 364; special education classroom = 226). The attendance indicator included 219 "not chronically absent," 94 "chronically absent," and 112 "unknown" observations after imputation. Influence diagnostics using Cook's distance identified no cases exceeding standard thresholds, suggesting no unduly influential observations. Taken together, these diagnostics indicated that assumptions for binomial logistic regression were reasonably satisfied, supporting the validity of the model's estimates.

Analysis for Research Question 1

The first research question examined which student-level and school-level factors were associated with the odds of graduating. Results from the binomial logistic regression analysis indicated that the full model improved significantly over the intercept-only model across all five imputations, as evidenced by omnibus likelihood-ratio tests, $\chi^2(25) = 132.610–147.311$, $p < .001$. Model fit was acceptable, with Cox & Snell R^2 values ranging from 0.268 to 0.293, indicating that the model explains approximately 26.8% to 29.3% of the variance in the outcome, representing a moderate level of explanatory power. Nagelkerke R^2 values from .401 to .439, indicate that the model explains 40.1% to 43.9% of variance in the outcome, suggesting moderate explanatory power. Calibration was adequate, as most Hosmer–Lemeshow tests were nonsignificant, and overall classification accuracy ranged from 82.4% to 83.1% across imputed datasets.

In the pooled estimates, several variables emerged as statistically significant predictors of graduation status. First, socioeconomic status (as indicated by qualification for free/reduced-price lunch) was a statistically significant predictor of graduation status ($B = 0.69$, $SE = 0.318$, p = .030). The odds of graduation were 1.995 times greater for those who qualified for free or reduced-price lunch than for those who did not, with a 95% *CI* of [1.070, 3.719]. Second, spending time in an alternative school emerged as a significant predictor of graduation status ($B = -1.07$, $SE = 0.396$, $p = .007$). Students who spent time in an alternative school had substantially lower odds of graduating than those who did not ($OR = 0.343$, 95% *CI* [0.158, 0.745]). In contrast, spending time in a general education classroom was a statistically significant predictor of graduation status ($B =$

1.361, *SE* = 0.46, $p = .003$). Students spending time in a general education classroom had 3.9 times the odds of graduating compared to those who did not spend time there (95% *CI* [1.583, 9.607]). Lastly, not being chronically absent was a statistically significant predictor of graduation status (*B* = 1.078, *SE* = 0.467, $p = .036$). Students who were not chronically absent had 2.938 times higher odds of graduation compared to students who missed > 10% of enrolled days in any observed year (95% *CI* [1.085, 7.961]).

The analysis also examined the relationship between the number of failed classes and high school graduation status. Students were grouped into three categories: those with no failed classes, those with one failed class, and those with more than one failed class. As shown in Table 6, students with one failed class were 2.309 times more likely to leave school without graduating than students with no course failures (*B* = .837, *SE* = 0.578, *OR* = 2.309, $p = .147$). Interestingly, students with more than one failed class had lower odds of non-graduation (*B* = -.344, *SE* = 0.368, *OR* = 0.709, $p = .350$) than those who failed no classes. However, neither finding was statistically significant at the $p < 0.05$ level. Although not statistically significant, the results suggest a potential relationship between academic performance and graduation outcomes, consistent with previous studies that have linked failure to dropout.

Other contrasts, including disability classifications, gender, race and ethnicity, grade retention, behavioral referrals, and most IEP service indicators, were not statistically significant at the .05 level in the pooled results. Small cell counts for certain categories (e.g., EL status = 1; separate special education school) were interpreted cautiously due to wider confidence intervals. Full results with *ORs* and 95% confidence intervals are reported in Table 6.

Table 6

Logistic Regression Predicting Graduation with Reference Groups

Pooled Estimates			95% *CI*			
Variable | Level	*B*	*OR*	Lower	Upper	*S.E.*	*p*
Disability						
Sensory/Communication				Reference		
Autism	.224	1.251	0.105	14.839	1.262	.859
Intellectual Disability	-.915	0.401	0.033	4.867	1.274	.473
Emotional Behavioral Disorder	.690	1.995	0.151	26.327	1.316	.600
Specific Learning Disability	.609	1.839	0.159	21.224	1.248	.625
Other Health Impairment	.705	2.023	0.180	22.723	1.234	.568
EL Status						
Non-EL students				Reference		.069
EL students	-2.443	0.087	0.006	1.212	1.344	
Gender						
Females				Reference		.361
Males	-.299	0.742	0.391	1.407	0.327	
Race and Ethnicity						
Black				Reference		
Hispanic	.433	1.542	0.400	5.937	0.688	.529
White	-.408	0.665	0.321	1.378	0.372	.273
Other/Unknown/Multiple	.385	1.470	0.350	6.173	0.732	.599
Socioeconomic status						
Did not qualify				Reference		.030*
Qualified	.690	1.995	1.070	3.719	0.318	
Failed Classes						
0				Reference		
1	.837	2.309	0.744	7.166	0.578	.147
> 1	-.344	0.709	0.344	1.459	0.368	.350
Grade Retention						
Not retained				Reference		.115
Retained	-.512	0.599	0.317	1.134	0.325	
Attendance						
Missed > 10% any year				Reference		
Not chronically absent	1.078	2.938	1.085	7.961	0.467	.036*
Behavior Referrals						
0				Reference		
1 – 3	.385	1.470	0.596	3.625	0.461	.403
> 3	-.639	0.528	0.240	1.162	0.403	.113
Consultative Service						
Did not receive				Reference		.244
Received receive	.590	1.805	0.668	4.879	0.507	

Table 6 (continued).

Pooled Estimates			95% *CI*			
Variable | Level	*B*	*OR*	Lower	Upper	*S.E.*	*p*
Co-Teaching Instruction						
Did not receive				Reference		.082
Received receive	.761	2.140	0.908	5.046	0.437	
Direct Instruction						
Did not receive				Reference		.467
Received receive	.311	1.364	0.591	3.152	0.426	
Supportive Service						
Did not receive				Reference		.213
Received receive	.429	1.536	0.781	3.020	0.345	
Alternative School						
Did not spend time				Reference		.007*
Spent time	-1.070	0.343	0.158	0.745	0.396	
General Education Classroom						
Did not spend time				Reference		.003*
Spent time	1.361	3.900	1.583	9.607	0.460	
Special Education Classroom						
Did not spend time				Reference		.153
Spent time	-.592	0.553	0.245	1.247	0.414	
Separate Special Education School						
Did not spend time				Reference		.572
Spent time	.395	1.485	0.377	5.854	0.700	

Note. Reference categories are the first categories listed in the Demographics and Descriptive tables. Odds ratios (OR) compare each non-reference level to its reference. All p-values are two-tailed Wald tests. Intercept omitted. * indicates significance at $p <$ .05.

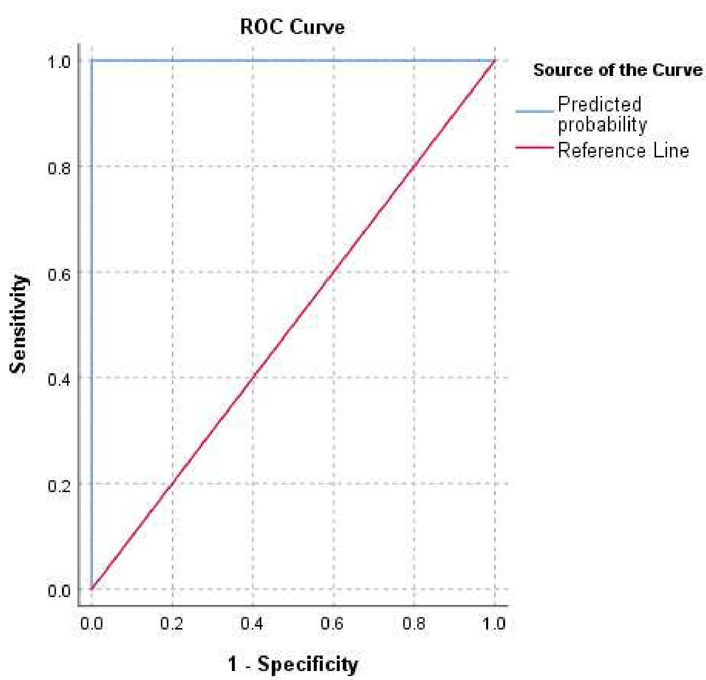
Using a .50 probability cutoff, classification accuracy across the imputed datasets ranged from 82.4% to 83.1%. Sensitivity for graduates (class = 1) was consistently high (92.6%–93.2%), whereas specificity for non-graduates (class = 0) was more modest (48.0%–51.0%), indicating that the models identified graduates reliably but were less effective at distinguishing non-graduates. Precision for graduates averaged .93, while precision for non-graduates was approximately .50, reflecting the sample imbalance (76%

graduates). Consequently, the weighted F1 favored graduate prediction, while the macro-averaged F1 highlighted weaker performance for the smaller non-graduate class.

Discrimination was strong. ROC analysis demonstrated excellent separation, with an area under the curve (AUC) of 1.00 in the final imputed dataset (95% *CI* [1.00, 1.00]; see Figure 2). Complementary fit indices (Nagelkerke R^2 = .401–.439) indicated moderate explanatory power. Overall, the models accurately predicted graduation status. However, the misclassification of non-graduates suggested that alternative cutoffs or cost-sensitive criteria might be warranted when early identification of students at risk of not graduating is a policy priority.

Figure 2

Receiver Operating Characteristic (ROC) Curve for the Logistic Regression Model (AUC = 1.000)



Analysis for Research Question 2

The second research question compared the out-of-sample predictive performance of four supervised classifiers: logistic regression, a multilayer perceptron (MLP) neural network, random forest, and a support-vector machine (SVM) with an RBF kernel in predicting high school graduation status. A 70/30 stratified train–test split was applied to maintain the graduation class distribution, and a .50 probability cutoff was used unless otherwise noted. Model performance was evaluated using accuracy, precision, recall, and F1 score for the positive class (Graduated = 1).

Overall, logistic regression achieved the strongest performance across most evaluation metrics (see Table 7). It achieved the highest overall accuracy (82.4%) and the best F1 score (0.889), narrowly outperforming the SVM (F1 = 0.884) and the MLP neural network (F1 = 0.881). The random forest model demonstrated slightly lower performance, with an accuracy of 77.7% and an F1 score of 0.861. Regarding sensitivity for graduates, the SVM achieved the highest recall (0.944), followed by the MLP neural network (0.941), logistic regression (0.929), and random forest (0.913). These results suggest that the SVM was slightly more effective at minimizing false negatives (i.e., graduates who were misclassified as non-graduates).

All models, however, performed less effectively in correctly identifying non-graduates at the default .50 decision threshold, reflecting the 76% class imbalance in the dataset. Specificity (true-negative rate) was relatively low across classifiers: logistic regression, 48% (49/102); SVM, 39% (40/102); random forest, 34% (35/102); and MLP neural network, 29% (8/28). This pattern suggests that the models prioritized overall accuracy and correct classification of graduates, but were less effective at flagging students at risk of not graduating. In summary, logistic regression provided the best overall balance of accuracy and F1 score, while the SVM offered the highest sensitivity for graduates. Improving the detection of non-graduates would likely require modifying probability thresholds or applying cost-sensitive classification methods, rather than changing the underlying algorithm.

Table 7

Predictive Performance by Model

Model	Accuracy	Precision	Recall	F1
Logistic Regression	0.824	0.852	0.929	0.889
Neural Network (MLP)	0.807	0.828	0.941	0.881
Random Forest (RF)	0.777	0.815	0.913	0.861
Support Vector Machine (SVM-RBF)	0.812	0.831	0.944	0.884

Notes. Metrics computed from SPSS outputs; positive class is Graduated = 1. The SVM and random forest metrics come from their SPSS confusion matrices; logistic regression metrics come from the SPSS classification table with cut = .50; the MLP metrics are from the model-metrics table provided

Summary

This chapter described the study sample, data preparation procedures, and the results of both research questions. The analytic sample included 425 students with disabilities from a single public school district. The majority of students were not English learners, nearly two-thirds were male, and the most common disability categories were other health impairment and specific learning disability. Data were obtained from administrative school records and screened in SPSS for missing values and accuracy of coding. Consistent with the analysis plan, IEP services and learning environments were coded as distinct yes/no indicators, as students may have received more than one service and educational setting. The attendance variable contained missing values; therefore, for Research Question 1, it was multiply imputed in SPSS using a logistic model. The primary measure was whether the student earned a regular diploma in four years.

For Research Question 1, the analysis examined which student-level and school-level factors were associated with graduation status. Four consistent patterns were observed in the multiple imputed results. Students who spent time in an alternative school had lower odds of graduating, while students who spent time in general education classrooms had higher odds of graduating. Students who qualified for free or reduced-price lunch were also more likely to graduate in this dataset. Moreover, students with disabilities who were not chronically absent were approximately three times as likely as their peers who were chronically absent to graduate from high school after controlling for other factors. Disparities were no longer statistically significant after controlling for disability classification, English learner status, gender, race and ethnicity, grade retention, behavior referrals, and most IEP services. Some of the categories had small sample sizes (e.g., EL status and separate special education school), which are imprecise, and should be interpreted with caution. The logistic model correctly classified about 82–83% of students and displayed excellent discrimination (area under the ROC curve = 1.00 in the imputed data). However, non-graduates remained harder to identify than graduates.

For Research Question 2, binomial logistic regression, a simple neural network (MLP), random forest, and a support vector machine (SVM-RBF), were trained on a learning set and tested on separate validation data in IBM SPSS Statistics using the same predictors. Logistic regression performed the best in terms of overall accuracy (82.4%) and F1 score (0.889), followed closely by SVM (accuracy = 81.2%, F1 = 0.884) and the

MLP neural network (accuracy = 80.7%, F1 = 0.881). As for random forest, a slightly lower performance was achieved (accuracy = 77.7%, F1 = 0.861). Sensitivity to graduates was high across all models, while specificity for non-graduates was lower and similar to the overall class distribution (≈76% graduated).

Chapter V

Conclusions, Implications, and Recommendations

Descriptive statistics, regression results, and predictive model performance were provided in Chapter IV. Chapter V presents these results in the context of existing literature, discusses implications for practice and policy, and offers suggestions for supporting SWD on the path to graduation.

Summary of Findings

The current study examined student-level and school-level factors associated with on-time high school graduation for students with disabilities, using several supervised learning models, and assessed the predictive validity of these models. Several key findings were found for both research questions.

First, in line with the existing literature highlighting the importance of school engagement and inclusive environments (Kart & Kart, 2021; Kurth et al., 2019; Reschly & Christenson, 2006), students who spent time in general education classrooms had substantially higher odds of graduating than those placed in alternative schools. Attendance also distinguished graduates from non-graduates, as chronic absenteeism was strongly associated with dropout risk, mirroring studies by Ritter (2015) and Blazer and Gonzalez Hernandez (2018), who reported that regular absenteeism is linked to academic disengagement and school dropout.

Demographic variables, including disability classification, English learner status, gender, and race and ethnicity, were not statistically significant predictors after statistically controlling for other factors. However, previous research has identified disparities across subpopulations in dropping out of and completing school (Dunn et al., 2004; Murnane, 2013; Zablocki & Krezmien, 2013). Notably, students eligible for free or reduced-price lunch had higher odds of graduating in this sample. This finding was contrary to national trends, which have traditionally associated lower socioeconomic status with lower completion rates (Ramsdal & Wynn, 2022; Wagner et al., 2014), and suggested the possibility of local interventions or targeted supports for economically disadvantaged students in this district.

Finally, results from Research Question 2 indicated that logistic regression provided the best overall prediction accuracy and was fully interpretable for practical decision-making, with a similar overall generalization ability to machine learning models, such as neural network, random forest, and support vector machine. This finding is consistent with previous studies (Bowers et al., 2013; Knowles, 2015), which suggested that linear statistical models may compete with complex algorithms for educational prediction tasks when sample sizes are moderate, and class imbalance makes it difficult to identify at-risk students (Kotsiantis, 2009).

Collectively, these results were a critical reminder of the fundamental role that attendance, placement in inclusive settings, and school-level interventions play in promoting graduation among students with disabilities, while also demonstrating the applied value of interpretable predictive modeling in early identification and intervention initiatives.

Discussion for Research Question 1

The first research question examined which student-level and school-level factors were associated with on-time graduation among students with disabilities. Several patterns emerged across various variables, including attendance, English proficiency, socioeconomic status, academic performance, school placement (learning environments), and other demographic factors.

Graduation Outcomes for SWD

One noteworthy finding from this study was the comparatively high graduation rate among students with disabilities in the participating school district. Nationally, students with disabilities continue to graduate at lower rates than their nondisabled peers, a pattern often linked to academic challenges, behavioral concerns, and systematic barriers. For example, the national four-year graduation rate for students with disabilities was 70.6% in 2020, compared to the overall graduation rate of 86% (NCES, 2015b, 2021b).

In contrast, the students with disabilities in this study graduated at a rate of 76% across the three cohorts examined. This rate exceeds the national average and suggests that students with disabilities in this district may be benefiting from conditions or supports that promote stronger outcomes. Several of the study's findings help provide context for this pattern. Factors such as consistent attendance, participation in general education settings, and access to socioeconomic supports emerged as significant predictors of on-time graduation. Taken together, these results point toward the role of inclusive practices, early and targeted interventions, and school-level supports in shaping graduation outcomes for this group. The sections that further explore these factors in more detail help explain why this district's results may differ from broader national trends.

While the results of this study align with previous literature, they hold particular relevance for rural educational settings. Rural districts often face constraints such as long transportation routes, limited community-based services, and reduced access to specialized supports, all of which may influence engagement and graduation outcomes for students with disabilities. At the same time, rural schools often benefit from strong community–school relationships, which may enhance student engagement and improve outcomes. The patterns observed in this study may therefore reflect the interplay between rural challenges and the unique strengths present within the participating district.

Attendance

Attendance was a key predictor of graduation outcomes. The odds of on-time graduation for nonchronically absent students were nearly three times those for students who had been chronically absent (B = 1.078, SE = 0.467, OR = 2.938, p = .036). This means that students who were not chronically absent had a much better chance of graduating on time. Specifically, their likelihood of graduating on time was approximately three times higher than that of chronically absent students. In other words, chronic absenteeism greatly reduced the chances of graduating on time. This finding highlighted how disengagement can start with something as simple as missed school days and lead to a pattern of poor academic performance and eventual dropout.

This result was consistent with Ritter (2015), who identified attendance as a key predictor of student engagement and the likelihood of graduating. Ritter noted that absenteeism often begins in middle school, worsens through high school, and leads to both academic and behavioral disengagement, thereby increasing the likelihood that a student will drop out without graduating. Similarly, Blazer and Gonzalez Hernandez (2018) examined data from Miami-Dade County Public Schools. They found that students with chronic absenteeism in the eighth to twelfth grade were between 6.6 and 8.6 times more likely to drop out than peers with better attendance. They also found that the risk compounded when absenteeism persisted across multiple years. Taken together, this evidence suggests that early identification and intervention measures for attendance problems, such as mentoring programs, home visits, or attendance incentives, can be essential to keeping students on track for graduation.

English Proficiency

The findings on English learner status were consistent with some prior research but contradictory to others. While national research typically found lower graduation rates among English learners compared to the overall student population (NCES, 2023b), Wood et al. (2017) found that English learner status was not a significant predictor of dropout once other predictors, such as poverty, academic risk, and school-level resources, were adjusted for. Also consistent with the current study, EL status was not statistically significant after controlling for attendance, academic performance, and school placement. This suggests that although language barriers may increase the risk of dropout in some instances, other factors, such as academic engagement and school-level factors, are stronger predictors of graduation.

Socioeconomic Status

An unexpected finding was in the results for socioeconomic status. Students who received free or reduced-price lunch were more likely to graduate ($B = 0.69$, $SE = 0.318$, *OR* = 1.995, *p* = .030), which contrasts with previous research showing that students with lower socioeconomic status typically have lower graduation rates and are at a higher risk of dropout. Ramsdal and Wynn (2022) noted that students from low-income families are disproportionately represented in dropout statistics worldwide. The National Center for Education Statistics (as cited in Blazer & Gonzalez Hernandez, 2018, p. 1) reported a nearly fourfold difference in dropout rates between the lowest and highest income brackets. Elbaum et al. (2014) found the effects of low socioeconomic status on graduation were almost two times as influential for students with disabilities as for peers without disabilities in Florida school districts. Similarly, Wagner et al. (2014) found that students from families with an annual income below $25,000 had just over half the likelihood of graduating compared with their peers from families with an income of $50,000 or higher (*OR* = 0.41, 95% *CI* [0.37, 0.45]).

The difference between the previous findings and the present results may be explained by the additional supports available within the local district. Schools serving higher proportions of students from economically disadvantaged backgrounds often receive Title 1 funding, which is specifically designed to provide supplemental academic support, early intervention, and targeted instructional resources to students identified as economically at-risk. In the participating district, many students receiving free or reduced-price lunch either attend, or have attended, Title 1 schools where such supports may include tutoring, mentoring, intervention programs, and access to social-emotional services. These evidence-based supports may have counteracted traditional risk factors associated with low socioeconomic status and, as a result, improve graduation outcomes for this population, contributing to higher graduation rates than those observed in broader national trends. Therefore, the higher graduation odds observed among students who qualify for free or reduced-price lunch may reflect the effectiveness of targeted Title 1 interventions that address both academic and non-academic barriers typically associated with this population. These findings suggest that, within this district, structured and well-implemented supports may help mitigate inequities commonly seen in larger national patterns.

Academic Performance

Course failure also emerged as an important, albeit not statistically significant, factor in predicting whether a student will graduate ($p = 0.147$ for one failed class; $p = 0.350$ for more than one). Students who failed a course were more than twice as likely to drop out compared to those with no course failures (OR = 2.309), and students who failed more than one course had odds approximately one-third lower ($OR = 0.709$). While these differences were not statistically significant, the pattern suggests that academic performance may affect successful graduation outcomes.

Existing studies found that course failure is one of the most powerful predictors of high school dropout. For example, Rumberger (2011) and Ritter (2015) emphasized that course failures in key academic subjects—especially those in the first two years of high school—are strong indicators of academic disengagement and are highly predictive of early school departure. Blazer and Gonzalez Hernandez (2018) also found that students who fail multiple credits over consecutive years are at a particularly high risk of dropping out, given the cumulative impact of academic gaps.

While the findings of the current study were not statistically significant, they were in line with previous research that has shown, over the years, how academic struggles often combine with other negative factors, such as truancy or behavioral issues, to predict graduation failures (Bowers et al., 2013). For school leaders, that underscored a need for early academic interventions, such as credit recovery programs, tutoring, or summer bridge courses, to ensure students do not fall too far behind. Early identification and intervention in course failure patterns can help reduce cumulative academic deficits, thereby decreasing the risk of dropout.

School Placement – Learning Environments

Attending an alternative school was significantly and negatively associated with graduating (B = -1.07, SE = 0.396, OR = 0.343, p = .007), aligning with previous research that shows alternative schools typically serve students who struggle behaviorally, academically, or with attendance (Lehr et al., 2004; NCES, 2002). Although alternative placements are intended to offer lower teacher-student ratios, flexible class schedules, and additional supports (Gilson, 2006; Lehr et al., 2004), other research findings indicated that students with disabilities can sometimes experience gaps in instructional continuity, which may be due to transition-related challenges in mainting the scope and sequence of tier-based curricular instruction or sealing new service delivery gaps after alternative setting transfer (Lehr et al., 2004). The present findings contributed to this literature by suggesting that, given the amount of time students with disabilities spent in alternative schools in this district, they may be at increased risk of low levels of on-time or educational completion than previously reported.

In contrast, general education placement was associated with higher odds of graduating (B = 1.361, SE = 0.46; OR = 3.900, p = .003). This was consistent with the Individuals with Disabilities Education Act's mandate for instruction to occur in the least restrictive environment (LRE) and with previous research documenting that inclusion promotes successful educational outcomes, social interactions, and access to grade-level curriculum (GaDOE, 2010; Kart & Kart, 2021; Kurth et al., 2019). Kart and Kart (2021) observed that students with disabilities who spend more time in general education classrooms are generally better off academically and socially than peers placed in more restrictive settings. Similarly, Schwartz et al. (2019) noted an overall positive impact on math and language arts achievement for students with learning disabilities who had integrated co-teaching and inclusive service models. Collectively, these findings underscored the value of participation in the general education classroom that allows students to experience peer modeling, exposure to rigorous curriculum, and collaboration among general and special education teachers (Friend et al., 2010).

Other Variables

Other student demographic variables (i.e., disability classification, gender, and race and ethnicity), grade retention, behavior referrals, and most IEP services were not statistically significant after controlling for other predictors. However, previous studies have pointed to important differences across subgroups. Studies by Dunn et al. (2004), Reschly and Christenson (2006), and Zablocki and Krezmien (2013) identified dropout rates of 26.7% for students with emotional and behavioral disorders, versus just 4.6% among those students with low-incidence disabilities such as autism, orthopedic impairments, or sensory impairments. Reschly and Christenson (2006) also noted that students with mild disabilities, including learning disabilities or emotional and behavioral disorders, demonstrated lower levels of school engagement as well as increased dropout risk compared to their non-disabled peers. The present results implied that when attendance, academic performance, and school placement are controlled for, demographic factors alone may be less related to graduation outcomes. Overall, the specificity of the logistic regression model was found to be 82-83% (good discrimination [AUC = 1.0]). Specificity for non-graduates was lower (~50%), suggesting that although the model is generally helpful, additional resources may be necessary to identify and intervene early with students who are less likely to graduate on time.

Discussion for Research Question 2

Accuracy and Interpretability

The second research question examined the predictive performance of four supervised learning models—binomial logistic regression, a multilayer perceptron (MLP) neural network, random forest, and a support vector machine (SVM) with a radial basis function (RBF) kernel—in predicting high school graduation status among students with disabilities. In line with existing literature, logistic regression performed well, outperforming all models in overall accuracy (82.4%) and F1 score (0.889), while remaining highly interpretable for educators and policymakers. The present finding was also consistent with those of Bowers et al. (2013) and Knowles (2015), who found that logistic regression remains a popular analysis technique in education data mining because it finds a balance between accuracy and transparency in high-stakes decision-making environments.

Recall vs. Accuracy Trade-Offs

Although the SVM model achieved the highest recall (0.944) for graduates, it did not show a substantial improvement in the overall classification accuracy, when compared to logistic regression or the MLP neural network, whose performance was very closely matched. These results were consistent with those reported by Márquez-Vera et al. (2016), who observed that machine learning approaches (such as SVMs and MLP neural networks) may provide marginal improvements in sensitivity or recall but are often contingent on larger datasets, parameter optimization, and technical expertise to outperform simpler models in educational settings. Likewise, Aulck et al. (2017) found that although both random forests and neural networks sometimes outperformed logistic regression in predicting school persistence, the improvements were often small unless the sample size was very large or rich longitudinal data were available. With moderate sample sizes and binary outcomes, such as graduation versus non-graduation, the findings of the current study suggest that logistic regression can be as effective as more complex machine learning methods.

Class Imbalance Challenges

Regardless of the models, one major issue in the current study was the misclassification of non-graduates. The specificity ranged from 29% to 48%, while the overall accuracy exceeded 80%, highlighting the known problem of class imbalance in educational prediction problems, where most students graduate (Bowers et al., 2013; Márquez-Vera et al., 2016). As noted by Kotsiantis (2009), for the case of a positive class (e.g., graduates) prevalence in the population, models tend to behave as if they can maximize sensitivity by labeling observations as members of the majority class and increasing sensitivity at any cost without thresholding probability or using cost-sensitive learning to avoid such a behavior on minority classes. The results of the current study also supportted this literature as, although the models did a reasonable job identifying graduates, they were weaker at identifying those who might not graduate, suggesting potential for exporing more appropriate cut points in the future that better reflect context, sampling approaches to collecting training data, or more innovatively employing cost-sensitive algorithms to balance classification towards the positive class.

Practical Implications

Finally, the strong performance of logistic regression in the current study highlighted the need for interpretability in educational settings. As Bowers et al. (2013) highlight, for predictive models in education to be useful and successful, they must not only achieve accuracy, but also assist educators by identifying student risk factors to allow the design of effective interventions. While complex models, such as neural networks, random forests, and SVMs, may yield small improvements in accuracy in some cases, their inherent lack of transparency can make it difficult for school leaders to understand how predictions are made, thereby limiting their usefulness for the early identification and support of at-risk students. The current results also reinforce recommendations by researchers such as Knowles (2015) and Márquez-Vera et al. (2016) to consider predictive performance alongside transparency and feasibility when recommending models for real-world educational decision-making.

Data Interpretation Limitations

Several limitations should be considered when interpreting the present findings. First, the research was limited to one school district in South Georgia, so the findings may not be generalizable to other schools with different demographics or policy environments. Similar restrictions were identified in studies by Dunn et al. (2004) and Zablocki and Krezmien (2013), which used state or national datasets, and acknowledged the limitations of sampling variance when examining subgroups of students with disabilities. Similar to those studies, the present analysis does not capture all district-level differences, such as quality of instruction or community resources, which may affect graduation outcomes.

Second, several variables, including English learner status, separate special education school placement, and certain disability classifications, had relatively small sample sizes, resulting in wider confidence intervals and less precise estimates. This issue has been observed in previous studies of dropout and graduation among students with disabilities (Reschly & Christenson, 2006; Wagner et al., 2014), where small subgroups limited the ability to detect meaningful differences and to detect trend evidence. This limitation could be better addressed in future studies using larger multi-district or state-level data.

Third, the present study was based on observational, historical data, meaning causal inferences cannot be made. As noted by Ritter (2015) and Blazer and Gonzalez Hernandez (2018), attendance, academic risk factors, and demographic characteristics may interact in complex ways, making it challenging to isolate individual effects without employing experimental or longitudinal strategies. For example, course failures and absenteeism can reciprocally reinforce each other, making it difficult to disentangle their independent effects on graduation outcomes.

Fourth, this sample was similar to other educational datasets (Bowers et al., 2013; Kotsiantis, 2009) in that it was imbalanced with far more graduates than non-graduates. This imbalance limited model specificity in predicting non-graduates, even within machine learning models, such as those previously identified in predictive modeling studies of education (Márquez-Vera et al., 2016). Similarly, the lack of longitudinal measures, such as year-by-year changes in attendance or course performance, prevented an examination of whether improvements over time reduced the risk of dropout.

Finally, the study was limited to administrative variables. It did not account for factors such as student perceptions, teacher-student relationships, and family involvement, which have also been reported to significantly impact high school graduation outcomes (Reschly & Christenson, 2006). Future studies that employ qualitative measures may help provide a deeper understanding of the context, experiences, and reasons behind students' decisions.

Implications for Practice

The findings of the current study have several critical implications for schools and district leaders to consider when examining how to improve graduation results for students with disabilities. These implications are important for rural districts, where geographic isolation, limited community-based services, and restricted access to specialized supports place greater responsibility on schools to meet the diverse needs of students with disabilities. At the same time, rural districts often benefit from strong community-school relationships, which may enhance the effectiveness of school-based interventions.

First, and as evidenced by the findings above, the current study, while limited, is highly aligned with Kart and Kart (2021) and Kurth et al. (2019), who both found a strong association between general education placement and graduation, reinforcing the importance of inclusive practices as mandated by the least restrictive environment provision. According to Schwartz et al. (2019), expanded co-teaching and collaborative models, as well as more integrated service models, will not merely have a direct impact on academic achievement but will foster a culture of belonging for students with disabilities. District leaders should prioritize professional development for teachers in inclusive strategies and ensure access to a high-quality curriculum for all students.

Another key consideration arising from the current study was the robust negative association between students' placement in alternative schools and graduation outcomes, suggesting that districts should review and reform policies on disciplinary removals, programmatic supports in alternative settings, and best practices for transitioning students back to their base schools. District leaders should ensure that alternative schools maintain high academic expectations, provide credit recovery opportunities, and facilitate reengagement planning to keep students on track for graduation.

Findings on chronic absenteeism align with those of Ritter (2015) and Blazer and Gonzalez Hernandez (2018), who identified attendance as a critical early warning indicator of dropout. District leaders should use data-driven early warning systems that incorporate attendance, academic performance, and behavioral data to identify students most at risk of dropping out. These systems can trigger timely, tiered interventions ranging from attendance mentoring to academic tutoring, allowing schools to address early signs of disengagement before they compound. In rural districts, attendance challenges may be increased by long bus rides, transportation barriers, and geographically dispersed communities. Rural school leaders may therefore need to develop targeted attendance initiatives that address the unique obstacles faced by students living in rural areas.

The unexpected positive association between free and reduced-price lunch eligibility and graduation within this district contrasts with national patterns reported by

Wagner et al. (2014) and Ramsdal and Wynn (2022), which typically indicate that socioeconomic disadvantage increases the probability of dropout. This may suggest that targeted interventions for economically disadvantaged students, such as mentoring or tutoring programs described in prior studies (Bradley, 2022), can help mitigate the negative effects of poverty on academic outcomes if implemented effectively. Further investment in this type of programming, along with initiatives to track and assess its impact, could improve graduation rates for students from low-income families.

Predictive modeling results were also consistent with the advice offered by Bowers et al. (2013) and Knowles (2015) on achieving a trade-off between model accuracy and interpretability in educational data mining. Although advancements in machine learning algorithms, such as neural networks or SVMs, sometimes yield better performance in large-scale studies (Márquez-Vera et al., 2016), their complexity may hinder their use in school settings. Logistic regression performed well in the current study. For early identification and intervention planning, it was appropriate to use clear, computationally straightforward models that schools can easily interpret and apply.

Taken together, these implications highlight the importance of school-based structures and proactive supports, particularly in rural districts where schools often serve as the primary or only provider of academic, behavioral, and social-emotional services. The combination of rural challenges and rural strengths suggests that rural districts may be well positioned to implement coherent, school-centered interventions that improve graduation outcomes for students with disabilities.

Recommendations for Future Research

Future research could expand on this work by combining data from multiple districts or states to enhance generalizability and facilitate subgroup analyses in more diverse settings. Future studies could compare rural, suburban, and urban districts to determine the extent to which the factors identified in the current study differ across demographic and policy contexts.

Given the rural setting of the current study, future research should also explore how rural-specific conditions affect the graduation outcomes of students with disabilities. Rural districts face distinctive constraints, including longer transportation routes, limited access to external mental health or academic support services, and greater geographical isolation, that may influence attendance, service delivery, and engagement. At the same time, rural schools may benefit from close community relationships. Understanding how these rural strengths and limitations, along with key predictors of graduation, could provide valuable insights into how rural districts can tailor interventions to better support students with disabilities.

More longitudinal research designs would be beneficial in understanding how academic, behavioral, and placement factors interact to influence graduation outcomes. Following students longitudinally over several years would enable researchers to investigate whether improvements in academic performance or non-academic performance, such as attendance or behavior referrals, lower the risk of dropping out, and whether early warning signs continue to predict non-graduation following such interventions.

Merging quantitative methods with qualitative data—such as interviews or focus groups conducted with students, teachers, and administrators—might help explain why certain statistical patterns emerged. For instance, the unexpected protective influence of free or reduced-price lunch status found in the current study may be driven by unmeasured supports, such as access to Title 1 services, tutoring, mentoring, or community-based programs. Qualitative research may reveal these latent processes and inform more targeted interventions.

Future research should also examine the specific role of Title 1 supports in shaping graduation outcomes for economically disadvantaged students. Investigating which components of Title 1 programming, such as intervention blocks, extended learning opportunities, or wraparound services, are most effective may help clarify why students from lower socioeconomic backgrounds in certain districts outperform expected trends reported in national literature. Comparative studies of Title 1 and non-Title 1 schools could further highlight the structural conditions that enhance or hinder the success of students with disabilities.

Methodologically, cost-sensitive machine learning models or adjusting decision thresholds may help identify students at risk of dropping out, particularly in imbalanced datasets. Comparing the trade-offs between local interpretability and global predictive accuracy in logistic regression, neural networks, and random forests could offer additional insight into the best approaches for educational settings that demand practical application.

Finally, research is necessary to evaluate the effectiveness of academic and behavioral supports for students in alternative schools and special education settings.

Controlling for these and other factors, and using causal identification strategies such as quasi-experimental design or randomized controlled trials, researchers can establish not just correlations but the true effects of a particular program targeting high-risk students, such as credit recovery programs, school-based attendance mentoring, or behavioral interventions, on the graduation rates of at-risk students.

Conclusions

The current study contributed to the growing body of research on factors influencing high school graduation among students with disabilities, while also evaluating the predictive performance of multiple analytic models. The results highlighted the positive impact of attendance and inclusion in general education classes on graduation status, demonstrating that both non-academic and environmental factors influence whether students successfully complete high school on time. The analysis showed that logistic regression had a better balance of accuracy and interpretability, nearly matching or exceeding that of other complex machine learning models, such as neural network, random forest, and support vector machine. These findings suggest that districts may employ relatively simple, transparent analytic methods to identify at-risk students, thereby avoiding the complexity and resource requirements associated with sophisticated machine learning algorithms. Such approaches are of interest to local areas with limited technological capacity but a need for early intervention systems, given the accessibility of these methods.

Equally important, the study had implications for potential policy and practice changes in attendance tracking, inclusive placement practices, and alternative education programs. Preventing chronic absenteeism, increasing access to general education settings, and establishing robust academic pathways for students in alternative schools are all actionable steps that can improve graduation outcomes. Ultimately, the current study showed that predictive analytics, when operationally combined with thoughtful interpretation and policy alignment, was capable of informing data-driven decision-making in education. By leveraging statistical evidence and practical interventions, schools and districts can better serve students with disabilities, reducing dropout risk while enhancing their postsecondary prospects. These findings provide a basis for further investigation, and future research should expand upon them using larger datasets across longitudinal designs and examining targeted interventions designed to increase the high school graduation rates of students with disabilities.

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Appendix A:

VSU IRB Approval

VSU IRB Approval

Institutional Review Board (IRB)
for the Protection of Human Research Participants

PROTOCOL EXEMPTION REPORT

Protocol Number: 04616-2025

Responsible Researcher(s): Missy Roddenberry

Supervising Faculty: Dr. E-Ling Hsiao

Dissertation Research Member: Dr. E-Ling Hsiao

Project Title: *A Statistical Examination of Factors Influencing Graduation Status of Students with Disabilities.*

Institutional Review Board Determination:

This research protocol is **exempt** from Institutional Review Board (IRB) oversight under 45 CFR 46.101(b) of the federal regulations, **category 4**. If the nature of the research changes such that exemption criteria no longer apply, please consult with the IRB Administrator (irb@valdosta.edu) before continuing your research study.

Additional Information & Guidance:

- *Research activities may begin at the Effingham County School District, according to the LOC signed by Dr. Yancy Ford (**06.23.2025**). Additional locations will be considered upon receipt of a letter of cooperation.*
- *Upon completion of the research study all data (e.g. data, transcripts, correspondence, etc.) must be securely maintained (e.g. locked file cabinet, password protected computer, etc.) and accessible only by the researcher for a **minimum of 3 years**. At the end of the required time, collected data must be permanently destroyed.*

☒ ***Proposed modifications must be submitted directly to the IRB Administrator at tmwright@valdosta.edu for review and approval. Implementing any modifications without written approval from the IRB is strictly prohibited.***

Elizabeth W. Olphie *06.18.2025*

Elizabeth W. Olphie, IRB Administrator Date

Thank you for submitting an IRB application.
Please direct questions to irb@valdosta.edu or 229-259-5045.

Revised: 06.02.16

Appendix B:

District Approval

District Approval

EFFINGHAM COUNTY BOARD OF EDUCATION

405 North Ash Street • Springfield, GA 31329 • 912.754.6491 • Fax 912.330.1590

Superintendent
Dr. Yancy J. Ford

Assistant Superintendents
Dr. Kirbi Ratner
Timothy Hood

June 18, 2025

Ms. Missy Roddenberry,

This letter serves as formal approval for Missy Roddenberry, a doctoral student at Valdosta State University, to obtain de-identified student data from the Effingham County School District for the purpose of her dissertation research.

Approval is granted for the release of the following de-identified datasets:

Student Record Student, SPED, Safety, and Enrollment extracts for fiscal years FY18, FY19, FY20, FY21, FY22, FY23, and FY24.

Student Class End-of-Year (EOY) extracts for fiscal years FY18, FY19, FY20, FY21, FY22, FY23, and FY24.

CCRPI Graduation Rate Files for fiscal years FY22, FY23, and FY24.

All student names and personally identifiable information will be removed prior to release. The files will be transmitted securely through the Georgia Department of Education (DOE) Portal Messenger system. We appreciate Missy's commitment to maintaining the confidentiality and security of district data and support her efforts to contribute to research that benefits students with disabilities.

Sincerely,

Yancy J. Ford

Yancy J. Ford
Superintendent
Effingham County School District
405 N. Ash Street
Springfield, GA 31329
(912)754-6491