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Exploring the Graduation Gap Between Oregon Virtual and Traditional High Schools

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By

Jeffrey M. Welch

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Abstract

The purpose of this causal-comparative study was to compare graduation rates, defined as completing high school within five years, of students who learned online in Oregon virtual schools to students who attended traditional schools. The study utilized longitudinal data provided by the Oregon Department of Education connected to literature-supported graduation indicators to explore and compare graduation rates of traditional and virtual students. Analysis of data in the study was guided by three research questions: (1) when examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits, (2) do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates, and (3) what combination of indicators is most useful for predicting a virtual student's graduation outcome? The analysis used descriptive statistics and binary logistic regression to address the research questions. Key findings of the study included: attending a virtual school was not a good predictor of whether a student would graduate; behavior was not an effective indicator in virtual schools; it was easier to predict a graduate than a non-graduate; adding measures of mobility to previously studied indicators, attendance, behavior, and course performance, improved the ability to predict graduation outcomes for both traditional and virtual students; for virtual students, results of this study suggest that mobility may be a valuable substitute for behavior in a predictive model focused on students who attend school virtually.

Keywords: Graduation, Virtual School, Dropout Indicators, Binary Logistic Regression

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The staff and faculty of the University of Portland who have been a support system, both seen and unseen, throughout this journey. From our first meeting, Dr. Randy Heatherington set the cohort on a path to a deep understanding of educational research and its historical scope. Dr. Nicole Ralston gave our cohort a baptism of fire in quantitative research methods. She then remained everyone’s biggest cheerleader as our cohort worked through the early stages of our dissertations.

My dissertation committee was excited by my research throughout, and their guidance was critical in helping me grow as a researcher. Dr. Greene provided insight that guided my work with thoughtful discernment of what many issues really meant. Dr. Weitzel, whose humor, kindness, and insight into leadership were always welcome. My chair, Dr. Waggoner, steered me through this process from beginning to end. From the moment I met with her to discuss my research, her enthusiasm for this project and her timely help made a tremendous difference in completing this dissertation.

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Preface

This study was conceived prior to the onset of the COVID-19 pandemic. This was an event that changed everyone's lives and with terrible consequences for many vulnerable people around the world. The participants in this study were unaware of COVID-19 or how it might impact them when the data were collected. However, the world of education was affected globally by COVID-19 and the other traumatic events of 2020. This year of tumult was the background soundtrack of the study presented here. It set the tone and magnified the potential gravity of what was written.

I became interested in graduation among virtual school students because in my own limited experience, I had observed two things: virtual school students seemed to have more struggles than brick and mortar students, and there was scant support in the literature about this discrepancy. While there was limited documentation of the discrepancy, explanations for why these students struggled were close to non-existent. I hope that this study and work that might follow it, from myself and others, will help enlighten all of us on the impact of virtual learning on long-term student outcomes in graduation and other elements of the students' education future life outcomes.

When I began this journey, I had no idea that every student would experience a form of virtual education that few teachers, schools, or students had had time to prepare for in a way that could do justice to the needs of students. The lockdowns moved schools almost overnight into a learning paradigm that was brand new to most teachers and students. This event has given us a new perspective on what school is and what school could be. More importantly, it showed us what we have lost when contact between teacher and student is strained and enlightened us on the tradeoffs we make when deciding where to send our children to school.

Both traditional schools and virtual schools have strengths and weaknesses as educational models. Those of us who have experienced both systems up close were already aware of each system’s benefits and deficiencies. Yet, as we move forward as educators, we have been reminded that we must be prepared to make changes to meet our students' needs. Each of us has directly experienced this through a unique event in world history. We have succeeded. We have failed. We have seen our shortcomings. However, it is doubtful that we could say that we have not grown through this experience. One hopes that our students would say the same thing. It is the hope that they will have a successful future that energizes educators and parents' work the world over.

~ *Jeff Welch, Portland, Oregon, May 2021.*

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Chapter 1: Introduction

Graduation rates and students dropping out of high school have been a long-time concern for policymakers and the taxpaying public. Many researchers have studied the topic, though no definitive consensus in either the causes or the solutions has been reached (Balfanz, Herzog, & Mac Iver, 2007; Bowers, Sprott, & Taff, 2013; Legters & Balfanz, 2010). One of the attempts to address improvements in student learning outcomes and graduation rates has been the movement to independently operated charter schools, which are publicly funded schools with reduced regulations on their operations to encourage innovation. Virtual schools are one of the innovations that have grown out of the charter school community. In these schools, students complete their learning away from a traditional school campus. As of 2019, 79% of students who attend school virtually in the United States were enrolled in a virtual charter school (Molnar et al., 2019). Between 2005 and 2019, charter school enrollment increased from 1.1 million to 3.3 million students, with 7,500 charter schools, and 219,000 teachers (National Alliance for Public Charter Schools, 2020). During the 2017-2018 school year, 33,677 Oregon students attended a charter school which was 5.9% of all public school enrollments (National Center for Education Statistics, 2019b). As of 2019, there were13,900 Oregon students that attended a virtual charter school (Oregon Digital Leaders Coalition, 2019).

Students learn in a classroom with a teacher present for most of their education in a traditional school setting. In a virtual school, students might only see their teachers or peers occasionally, through video conferencing applications, or not at all

(Barbour & Reeves, 2009; Molnar et al., 2019). With this situation in mind, it is crucial to understand that the impact of virtual schooling is not adequately understood from the existing literature. Virtual schools and related studies are growing in number, but more research is needed to keep up with the changes (Arnesen, Hveem, Short, West, & Barbour, 2019).

By the 2019-2020 school year, enrollment in Oregon virtual charter schools had increased to 13,900 students. (Oregon Digital Leaders Coalition, 2019). Both charter schools and virtual schools have had their performance questioned (Wang & Decker, 2014). Test results have not been significantly better for charters, and graduation rates have been lower for Oregon virtual schools (Betts & Tang, 2016; Oregon Department of Education, 2020a; Rapa, Katsiyannis, & Parks Ennis, 2018). As virtual schools continue to expand, with underwhelming results not appearing to dampen enthusiasm for them, studying the roots of performance differences is necessary (Rapa et al., 2018; Wang & Decker, 2014).

Statement of the Problem

Compared to other states, Oregon has a long history of poor graduation rates for high school students, which consistently lag behind the national rate (see Table 1). Between 2008 and 2019, Oregon graduation rates were an average of 9.7% lower than national rates (National Center for Education Statistics, 2018b; Oregon Department of Education, 2021).While improving graduation rates has become a national concern in the educational reform movement, Oregon students' improvements continue to trail the successes seen at the national level. Many solutions have been proposed to address performance issues in schools. A reform that was implemented in many states was the introduction of charter schools, which it was argued, could innovate and develop new methods of learning. Successful innovations would subsequently be integrated into the broader educational system (Lester, 2018; Lubienski, 2004). Virtual schools are primarily offered by charter operators. In this model, students learn with online coursework using laptops and the internet as their learning environment. While students may sometimes appear in person for certain activities or classes, most of their time learning is away from what would be typically recognized as a traditional school.

Table 1

Oregon and National Graduation Rates by Percent

		Oregon All Students		Oregon Virtual Students	
High School Start	Graduation Year	Four-Year	Five-Year	Four-Year	National Rate
2013-2014	2016-2017	76.7	80.0	46.9	85.3
2014-2015	2017-2018	78.7	81.6	57.1	85.5
2015-2016	2018-2019	80.0	*	*	87.1

Note. Adapted from the National Center for Education Statistics, 2018a, 2019; Oregon Department of Education, 2018, 2019, 2020a, 2020d.

* Not available.

The idea of innovation in education is popular with the public and with educational reformers. However, there is a dark cloud hanging over virtual high schools in Oregon. The state of Oregon's graduation rate is low in comparison to other states. In 2016-2017 Oregon ranked 49th out of 51, comparing all states and the District of Columbia (National Center for Education Statistics, 2018b). The graduation rate of Oregon’s virtual high schools was even lower. Oregon high school students who attend school in virtual school settings have substantially lower graduation attainment when compared to all students in Oregon (Oregon Department of Education, 2020a). For the Class of 2018, the four-year graduation rate was 32% lower for virtual students compared to the state as a whole (Table 1). The literature indicates that students taking courses in physical classrooms and online settings have similar learning outcomes; it would follow that graduation rates would also be similar for virtual and traditional students, but this is not the result that is seen in Oregon (Cavanaugh, 2009; Cavanaugh, Gillan, Kromrey, Hess, & Blomeyer, 2004; Means, Toyama, Murphy, & Baki, 2013; Means, Toyama, Murphy, Bakia, & Jones, 2010; Oregon Department of Education, 2020a). Thus, a gap in research exists between what the literature predicts should be equivalent learning outcomes in courses, and the graduation gap seen between virtual and traditional schools. The state of Oregon had a four-year graduation rate of 79% for the 2017-2018 school year (Oregon Department of Education, 2020b); virtual schools had substantially worse graduation rates. Of the 15 Oregon virtual schools, the median-performing district had a 61% five-year graduation rate, with six of Oregon’s virtual schools graduating less than 50% of their students within five years (Oregon Department of Education, 2020a). However, it is not clear why virtual schools perform so much lower in graduation rates.

Purpose Statement

The purpose of this causal-comparative study is to compare graduation rates, defined as completing high school within five years, of students who learned online in

Oregon virtual schools to students who attended traditional schools. To obtain an Oregon diploma and be defined as *graduating*, students must accumulate 24 credits in the specified content areas. There are other kinds of high school completions that are excluded from this definition: students who completed a GED or an Extended Diploma are not counted as graduates under this study's parameters (Oregon Department of Education, n.d.). Student attendance data will be used to determine what percentage of their school attendance was in a virtual school based on the student's *average daily membership*, an attendance measure that the state of Oregon uses for attendance, and records separately for each school attended. Also, other graduation indicators will be examined.

Research Questions

This research study will document if there is a discrepancy between the graduation outcomes of Oregon's virtual and non-virtual schools, as preliminary research suggests, by investigating the following research questions. The causal-comparative methodology is appropriate when two groups need to be compared, but a variable is different between the two groups (Mills & Gay, 2019). In this study, the dissimilar variable was the student's school setting, virtual or traditional.

Research Question 1: When examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits?

Research Question 2: Do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates?

Research Question 3: What combination of indicators is most useful for predicting a virtual student's graduation outcome?

Overview of Research Design

This study utilized longitudinal data from the Oregon Department of Education that corresponded to indicators identified in the literature that show the most reliable research basis for predicting if a student will successfully graduate from high school within five years. The study added the additional factor of attendance at a virtual school to analyze the effects of the virtual environment on the prediction for graduation from high school within five years.

Conceptual Framework for the Study

This study will use prior research on early warning indicators as the conceptual framework for this current investigation. While Phinney (2016), Mac Iver and Messel (2013), and Rumberger and Lim (2008) did not look at virtual schooling as a graduation factor, layering the choice to attend a virtual school on top of their prior work can provide insight into the effect of virtual environments on Oregon's high school graduation rates. Phinney (2016) completed the most current research on early warning systems applied in Oregon. Phinney's work relied on Mac Iver and Messel (2013) and Rumberger and Lim (2008) to establish a theoretical framework. The work of Bowers et al. (2013) will also be utilized; it compared 110 indicators from 36 different studies to determine which were the strongest risk factors in predicting graduation within five years of starting high school. This study will then match the strongest indicators to the available data to create a model for understanding how the virtual school setting interacts with other predictive factors (i.e., attendance, behavior, 9th-grade on-track, overage, mobility).

Significance

The study has the potential to provide benefits to many educational stakeholders. Policymakers and legislators determine the laws and rules that govern schools and decide how to allocate resources. It is the duty of policymakers and legislators to see that public resources are well spent and that the state's rules and standards are upheld in all public schools, whether traditional or virtual. Educators will benefit by increasing their understanding of the effectiveness of virtual schools in contrast to traditional schools. If the schools are effective, this can justify the choices that have been made. If it turns out that virtual schooling is itself an indicator that results in decreased graduation outcomes, the study can point out to school leaders problems that need to be addressed.

Researchers can benefit from this study by having access to analysis of how students in virtual schools compare to their traditional school peers in the state of Oregon. As it now exists, the literature does not give a clear answer to why students in virtual settings have worse five-year graduation outcomes. Using descriptive statistics to describe the population of students in virtual and traditional schools in Oregon and analyzing their performance indicators before graduation, this study may illuminate whether attending a virtual school or student preparedness for high school is more impactful on graduation outcome. Additionally, there is little literature specific to graduation rates in Oregon and the state's unique needs and assets. Oregon data were included in studies inclusive of U.S. states, but few published sources address Oregon graduates in detail (Phinney, 2016; Rumberger, 1987, 2011).

Most importantly, this study has the potential to benefit students and families that support them. Since attendance at a virtual school was a voluntary decision, this study's results could give students and families comfort that they have made a good decision in their educational choice. Families have limited data that they can count on in understanding the quality and effectiveness of schools, particularly virtual schools. Knowing more about virtual schooling's effects on learning and graduation will only become more valuable as a larger population of students participate. Alternatively, the results may indicate to families that they need to give increased scrutiny to their student's school or consider other options if a non-traditional placement is required.

While preliminary research indicates that a higher percentage of students graduate from traditional schools than students in virtual schools, the literature is nearly silent on why (Molnar et al., 2019; Oregon Department of Education, 2018, 2020a). It could be theorized that instruction was better in traditional school settings or that students in virtual environments were less well prepared upon entering high school, which resulted in a lower successful five-year graduation rate. The former is beyond the scope of this study. However, this study will try to inform the latter possibility by shedding light on whether the students that self-selected the virtual environment were less prepared for high school than their traditional peers. Until the Spring of 2020, virtual settings were primarily offered by charter schools. Students and families decided not to attend a traditional school and substitute a virtual school. There are many reasons why a family could make this choice. Still, the decision of less well-prepared students to attend may influence whether the student attending the virtual school is likely to succeed and impact five-year graduation outcomes (Means, Bakia, & Murphy, 2014).

Summary

This chapter discussed the need for a more thorough understanding of the difference in graduation rates for students who attend virtual and traditional schools in Oregon. Graduation rates are worse for Oregon virtual schools when compared to traditional schools (Oregon Department of Education, 2018, 2020b). It also discussed the research gap, while previous studies have indicated that students in virtual and traditional settings have had similar classroom learning outcomes, Oregon's data suggest that graduation rates are not similar when comparing traditional and virtual schools. The outcome difference is not accompanied by an understanding of the students that attend school in these two distinct settings. There is no good understanding of how the students might be different, particularly how well students were prepared to succeed in high school upon enrollment.

This study may benefit many stakeholder groups: policymakers, educators, parents, and students. With the growth of virtual schooling, stakeholders need a better understanding of virtual schools' role in moving students toward successful graduation. The lack of clarity on whether the virtual school setting itself is a factor in predicting five-year graduation rates or if students who are less prepared for high school have self-selected virtual schooling makes it difficult to determine what changes, if any, need to be made in improving the performance of virtual schools.

Chapter 2: Literature Review

The literature synthesized below provides background information on graduation rates, virtual schools' performance, and life outcomes for non-graduates. The chapter begins with a historical overview of graduation rates and how they have changed in the United States since 1870. There is a discussion of virtual schooling and why some students see it as an escape from traditional school. Next, there is a discussion of the graduation outcomes of virtual and traditional students. Strategies for improving graduation rates and specific information related to the state of Oregon's unique situation are then examined. The literature on early warning indicators, as applied in high school graduation, is reviewed. It delves into the various ways that researchers have tried to understand and predict who would drop out of high school by exploring multiple attempts to explain and identify which students would graduate and which would not. Finally, there is a discussion of the research gap and a conceptual framework for the study.

Historical Background of High School Graduation

Before the American Civil War, graduation from high school was rare. Figure 1 shows the changes in graduation rates in the United States since 1870.

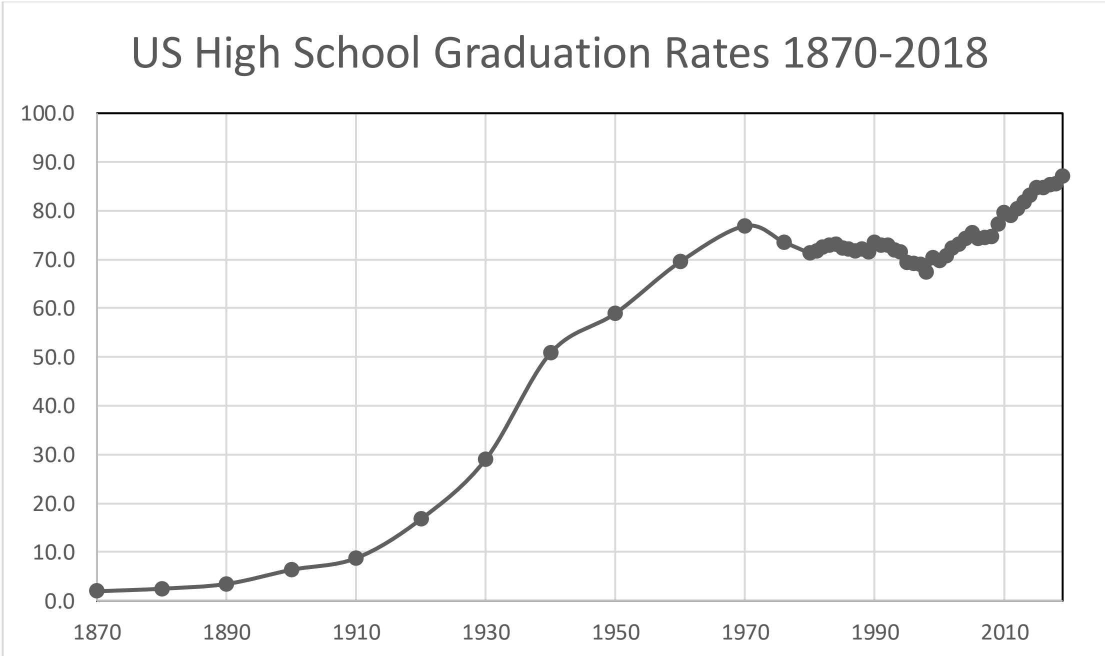

Figure 1. United States High School graduation rates from 1870-2018, all students as a ratio of the 17-year old population. The graph includes imputed data for missing states in 1990, 2003, 2006, and 2009. Estimated data for 2014 through 2018. Adapted from the National Center for Education Statistics, 2018a.

In the first year with available graduation data, 2% of the 17-year-old population completed high school. Over the next four decades, the figure rose gradually, nearing 9% in 1910. From 1910 to 1940, there was a very rapid rise in graduation attainment in the United States, reaching 51% on the eve of the U.S. entry in World War 2. The post-war period saw a decline in the rate of increase with a postwar peak in 1970. Subsequently, there was a decrease in graduation attainment, which plateaued between 1980 and 2001, graduation rates in this period hovered near 70%. In the first two decades of the new millennium, graduation rates have consistently improved, with the national rate reaching 87% in 2018 (National Center for Education Statistics, 2018a).

This recent improvement in graduation rates represents an impressive achievement for the nation's early adult population.

In 1960 the United States had the highest high school graduation rate among Organization for Economic Co-operation and Development (OECD) countries. By 2000 it was 13th out of 19 countries (Murnane, 2013). Sliding this far in the ranking resulted from improvements in other nations, while rates in the United States remained mostly the same.

Long Term Life Outcomes from Graduation Attainment

Educational attainment of a college degree has been thought of as the gateway to a middle-class lifestyle in the United States. The lack of graduation from high school has been a gatekeeper that prevented the continuation of education and entry or advancement in the workforce. There is a high cost to school dropouts, including lost opportunity, lower incomes, and increases in at-risk behavior participation (Campbell, 2015; McDermott, Anderson, & Zaff, 2018; Zaff et al., 2017). Murnane (2013) studied the economic impact of dropping out compared to attaining a high school diploma with data broken down by race and gender. The mean hourly wage of male high school graduates was approximately 50% higher than students who had dropped out in 2009. The wage gap was consistent for males back to 1970; females' wage gap widened from 30% in 1970 to 40% in 2009. College graduates of both genders earned substantially more. Male dropouts were unemployed more often than their high school graduate peers (McCaul, Donaldson, Coladarci, & Davis, 1992). Dropping out of high school increased the chances that adults would abuse alcohol, have limited voting participation, and be less physically active. Becoming a dropout was connected to being disassociated from adult norms, community organizations, and the levers of citizenship (McCaul et al., 1992).

The economic consequences of dropping out of high school are severe. Still, there is little research that shows if dropping out causes negative economic consequences or if it is an effect of the student's upbringing. To clarify this question, Campbell (2015) examined the results of dropping out of high school by comparing life outcomes for siblings, one who dropped out and another who completed high school. The author agrees that students who drop out faced increased difficulty in life. However, he questioned whether it is the fact that the student dropped out that causes the more complicated life or whether an already difficult life led to the student dropping out. He argues that there is little research that explains which is the cause and which is the effect. Since disadvantaged students are overrepresented in the dropout population, this group was likely to struggle whether they completed high school or not. In the analysis of sibling differences in economic terms, the author established that a sibling who dropped out was likely to earn less, work less often, and be more likely to be in poverty than a high school graduate from the same family. While early-life economic hardships can also negatively impact the student's future economic prospects, the lack of a high school diploma is a contributor to later life economic difficulties.

High school dropouts have difficulty being hired for jobs, earn less money, have fewer promotion opportunities, and tend to be in low-skilled professions. They are more likely to be incarcerated, involved in crime, or become dependent on government financial assistance (Christle, Jolivette, & Nelson, 2007). No matter its antecedent, not completing high school increases the non-completers chances for a grim future for themselves and their children.

Escaping to Virtual Schools

In virtual school settings, graduation rates have been found to be lower than in traditional settings. In some cases, these differences are substantial. Montgomery (2014) compared the graduation rates of full-time students attending virtual schools in South Carolina to traditional students. The study focused on low-socioeconomic students. The results found that the students studied did significantly worse when enrolled in virtual schools than similar students in traditional schools. Montgomery (2014) explained that there are many reasons that students chose a virtual school; some were not well prepared to be successful, and "…there are also students who enroll in virtual school as an escape from brick and mortar school" (p. 2). Students who were escaping were looking for a school that did not meet during typical school hours, had a curriculum perceived as easier, or wanted to avoid direct interactions with teachers, according to Montgomery (2014). The research tried to determine if low socio-economic status or high poverty rates among students were determinative of lower graduation rates in virtual schools compared to the rates at traditional schools. In this study, these factors were not significant. The results called the effectiveness of virtual schools in South Carolina into question.

There are many reasons why students might choose a virtual setting: flexibility, difficulty in transportation, choice in the curriculum, lack of success in their education, or social conflict in their previous school. Schnase (2011) conducted a quantitative study to determine if race, gender, reading level, months enrolled, or credit deficiency impacted students' graduation rates in a virtual school. The study found that only credit deficiency at enrollment and length of time registered were determinative of likely success in graduation. Credit deficiency and alternative settings are a factor for some students entering virtual schools. They may have had difficulties in traditional schools that they, or their parents, may have hoped a virtual school could avoid. Schnase (2011) lists low-quality traditional schools, high poverty communities, poor behavioral choices from peer influence, and avoidance of challenging courses as reasons students have chosen virtual schools as alternatives to traditional schooling. A large number of ‘alternative’ students may have pushed down the graduation rates of virtual schools. Alternative schools have been places where students who have not succeed in a traditional high school setting attempt to get back on track.

Alternative schools offer separate learning environments that give struggling students different avenues to complete their education. Students in these schools have fallen behind their peers and may be deficient in credits or exhibiting other at-risk behaviors. The alternative school’s role is to give the student an opportunity to move forward and persist in their education (Bomotti, 1996; Knesting, 2008). Even for traditional schools, virtual learning has been utilized in a credit recovery mode to fill gaps in learning for traditional students (Powell, Roberts, & Patrick, 2015). For high school students, there is a spectrum of interventions that are offered depending on a students learning needs or how far behind in credits they have become. They may be offered counseling, tutoring, summer school, night school, or be fully shifted into an alternative school setting to provide for their entire education. As a student's needs grow, the interventions become greater. Virtual charter schools may be acting as an additional alternative school beyond the options available in individual districts (Montgomery, 2014; Tuck, 2014). Virtual charter schools are ideally suited to take on this role as they are designed to be more flexible and tailored to the needs of individual students. However, having students with greater needs will also impact the performance measures of virtual schools when they are compared to traditional institutions. If these students have moved in large numbers toward virtual schools, this could be a large piece of the explanation for their lower graduation attainment. Unfortunately, this is an area that lacks adequate research and needs further study to clarify these issues.

Wang and Decker (2014) examined the performance of virtual students attending school in Ohio. The authors noted that unlike in some other states, Ohio's virtual school demographics indicated that marginalized students were overrepresented. Students who were behind in credits, had disabilities, and students that were of lower socioeconomic status were attracted to Ohio's virtual schools in large numbers. The authors noted that these marginalized groups have lower academic achievement in all settings, so their overrepresentation in Ohio virtual schools unsurprisingly would influence lower performance levels compared to schools with fewer marginalized students. In examining virtual schools' performance, care must be taken to see if students are demographically comparable to the comparison peers. Even though Ohio virtual schools had lower performance, the schools are still growing despite their subpar achievements.

Educational Outcomes for Students in Virtual and Traditional Settings

Virtual charter schools' growth has outpaced the literature that has evaluated their effectiveness (Cavanaugh, 2009). In a meta-analysis, Cavanaugh et al. (2004) examined the impact of online learning on student outcomes compared to students in traditional learning environments. The study showed that using web-based learning tools was comparable to those of students learning in traditional classroom settings. Distance learning was found to be neither better nor worse than other school settings. The study included data from 10 virtual charter schools. The schools' performances in the study were equivalent to traditional schools, while the performance of contemporary non-virtual charters was found to be lower than that of traditional schools. In a study of factors that influenced student success in learning Algebra one in online settings, Liu and Cavanaugh (2012) identified student time in the course as measured by the LMS (learning management system) and higher levels of feedback from the instructor as factors that were positively correlated to student success. These factors imply the importance of student engagement in the course material, student to teacher communication, and teacher monitoring of student performance as influential factors in student success.

Improving Graduation Rates

If graduation rates are to be improved, schools must identify strategies to maximize their students' success. In a review of 25 years of research on factors that predict successful completion of high school, Zaff et al. (2017) identified 12 ‘assets,’ which suggested that students would be successful and identified several others that needed further study. Assets that suggested a likely graduate included the student’s level of motivation, engagement with the school, parental involvement, and connection to peers and staff. The findings support the idea that schools can work to create a supportive environment where relationships are strengthened. There would remain many areas out of the school's control, but increased connections in the school community can influence outcomes. This review was broadly focused on graduation and not online learning. Still, it has implications for online schools in the elements that could be missing from their programs, which might promote successful students.

Teacher and students’ relationships are a strong factor in leading to student success. A study of the relationship of teacher to student interaction on course completion and academic performance as measured by the end of course grades did not find a connection between final grades and interaction; however, it did find a connection between the quality and frequency of interactions and student course completion (Hawkins, Graham, Sudweeks, & Barbour, 2013). More frequent and high-quality interaction led to higher class completion; course completion is a known factor that predicts graduation (Allensworth & Easton, 2007; Balfanz et al., 2007; Kupersmidt & Coie, 1990; Silver, Saunders, & Zarate, 2008). The school studied by

Hawkins et al. (2013) was a state-wide virtual high school using self-paced study and asynchronous teaching methods, which means students study at a time of their choosing and do not have to be at school during at a specific time. They found that "Higher quality interaction and more frequent interaction scores increased the log odds of completion significantly. In other words, students who completed the course perceived greater interaction and quality of interaction than noncompleters" (Hawkins et al., 2013, p. 78). This study has implications for how virtual schools design their interactions with students, which may be one of the most important ways of increasing course completion, and ultimately improving graduation rates. The results indicated that students' perceived quality and quantity of interaction between teachers and students had a determinative impact on the successful completion of courses. Other research supports the idea that student agency leads to more impactful student engagement and better outcomes (Klemenčič, 2017). Virtual schools may be able to build upon student agency and individualized curricular choices to improve their performance.

Oregon's Graduation Rates

Research that is specific to Oregon, or even more broadly to the Pacific Northwest, is limited. The most common place to find research on Oregon graduation rates is in broad examinations in the United States, which include results by state, but do not directly address issues at regional and state levels (National Center for Education Statistics, 2018b; Rumberger, 1987, 2011).

The most relevant regional research applicable to this study was completed by Phinney (2016), which used student data to create and test an early warning system that would predict high school graduation or non-completion in a specific school district in Oregon. Phinney's research utilized the ABC (attendance, behavior, and course performance) on track framework, as outlined by Mac Iver & Messel (2013), to determine which factors to analyze in the predictive model. The model was able to predict graduate/non-graduate with a 69% accuracy. Phinney found that attendance measures, behavior as measured by office referrals, coursework, and identification as a special education student were strongly predictive. Demographic factors, like race and gender, were not found to be predictive.

Data sets comparing Oregon to other states show that Oregon is doing poorly compared to other states. Figure 2 shows a national picture of graduation rates; only the District of Columbia and New Mexico graduated fewer students in four-year graduation comparisons for the Class of 2017. Data were available from the state of Oregon that details graduation rates at the school and district levels from state created databases and reports (Oregon Department of Education, 2018, 2020b).

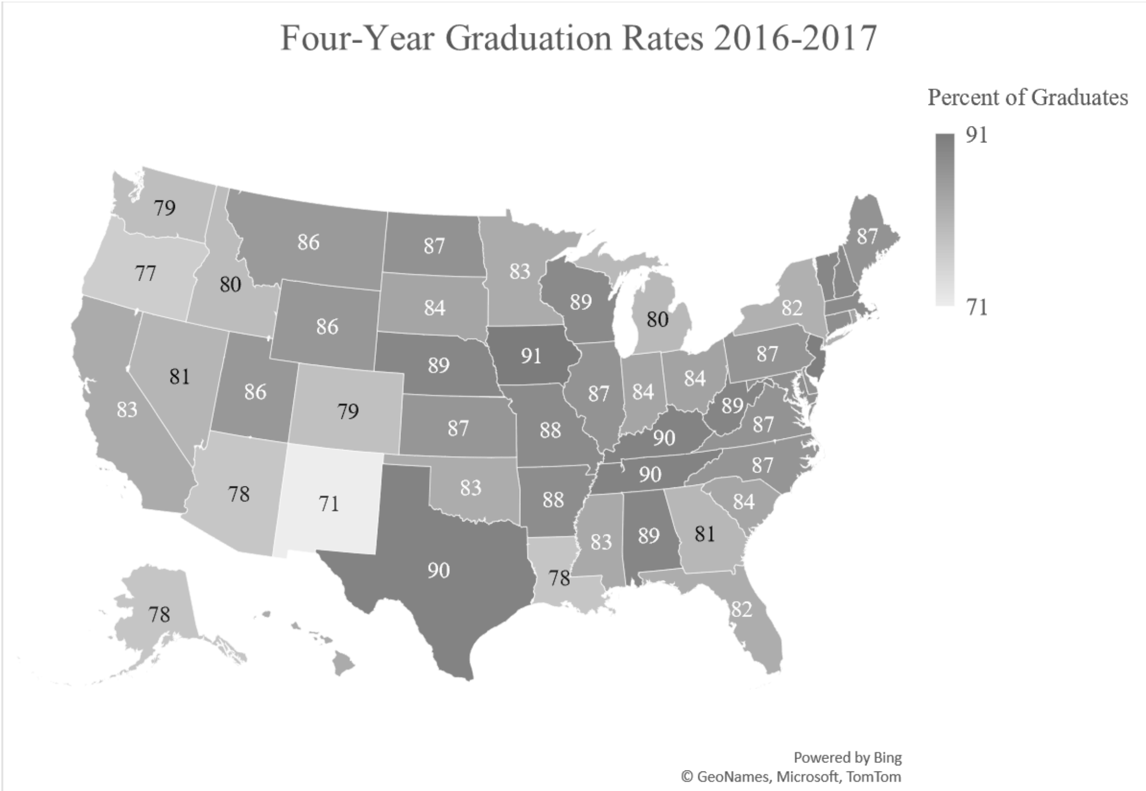

Figure 2. Four-year graduation rates by State and the District of Columbia. Adapted from the National Center for Education Statistics, 2018b.

Oregon's comparison to other states in Figure 2 demonstrates the need for continual vigilance of policy makers and educators on the issue of graduation. While the state has had a gradual improvement over time in its graduation rate, it continues to be near the bottom of all states.

Graduation Early Warning Indicators

In trying to predict which students are potential dropouts in early warning systems, specific factors or combinations of factors must be determined that are most likely to result in a possible school exit before graduation. The early years of high school have been identified as critical in whether students choose to exit schooling.

Determining if a student is likely to drop out is vital. Doing so by the end of 10th grade leaves open opportunities for interventions that may be successful (Battin-Pearson et al., 2000). Bowers (2010) found that students began to drop out as early as the 7th grade, with a peak risk of dropping out between 8th and 11th grades. The most likely years to dropout are grade 8 before the beginning of high school and grade 11 when students are old enough to drop out. The sooner that a school can identify a potential dropout and implement an appropriate intervention, the more likely that the student can be redirected. Interventions guided by early warning indicators have been found to increase attendance, course performance, and improve graduation rates (Davis, Mac Iver, Balfanz, Stein, & Fox, 2019).

Attendance. Attendance is strongly associated with a student's likelihood of completing high school (see Balfanz et al., 2007; Ekstrom, Goertz, Pollack, & Rock, 1986; Kupersmidt & Coie, 1990; Mac Iver & Messel, 2013). More specifically, absenteeism is a strong predictor that a student is likely to drop out (Balfanz et al., 2007; Mac Iver & Messel, 2013; Silver et al., 2008). Poor attendance indicates low levels of engagement with school and may indicate other problems that students are facing outside of school.

Behavior. Student behavior, including suspensions from school, have also been found to be predictive (see Balfanz et al., 2007; Ekstrom et al., 1986; Mac Iver & Messel, 2013; Suh & Suh, 2007). Student misbehavior implies disengagement or estrangement from the school as an institution. In Oregon, Phinney (2016) identified behavior incidents as a strong indicator that students were likely at risk of failure to complete high school. The cause of the misbehavior may be a result of things happening in the student's life outside of the school environment (Doll, Eslami, & Walters, 2013). However, it is a strong indicator that a student may be at risk of not completing their education. Situations vary for each student, so it is not certain that schools can successfully intervene. Still, high levels of disciplinary problems should result in a school paying careful attention to a student's long-term performance and providing interventions to the student that can allow the student to reengage with school (Mac Iver & Messel, 2013).

Performance factors. Performance factors are those that are related to what students know and can do. These include such things as course completion, classroom grades, GPAs, and standardize test scores. Numerous studies have found a connection between these factors and the student's ultimate likelihood of graduation (Battin-Pearson et al., 2000; Bowers, 2010; Hammond, Linton, Smink, & Drew, 2007). Teacher-assigned grades have been found to be highly predictive of a student's risk of becoming a dropout. This finding is even more surprising since the teacher's assessments are sometimes considered to be subjective.

Battin-Pearson et al. (2000) examined five different theories that might predict dropouts before the 10th grade. The models were compared to determine what the best predictors of dropping out might be. By far, the strongest predictor in their study was low academic achievement. Factors like gender, race, socio-economic status, poor connection to the school, and parents' attitudes toward their children's education were included in the models that were developed. While these factors added a small increase in the accuracy of the models, it was clear that academic achievement was the factor of most importance. Their research suggested that to develop dropout preventing interventions, performance should be a primary focus.

Course grades are the determining means of evaluating if students have completed courses. Course completion or failure has been utilized to generate on-track measures to create early warning systems for potential students dropping out of high school (Allensworth & Easton, 2007). Students in the Los Angeles Unified School District who failed two classes in middle school or 10% of their high school classes were found to graduate a fifth as often, or half as often, respectively, compared to their peers (Silver et al., 2008). Allensworth (2013) documents the early creation of a 9^{th}-grade on-track early warning system developed by the Chicago Public School system. Using only the on-track indicator, CPS achieved a sensitivity of 80% (true positives) and a specificity of 72% (true negatives). Adding in other demographic factors, test scores, and GPA only increased sensitivity to 81% while it did not improve specificity. Thus, being on-track alone gave almost a complete picture of who would be likely to graduate or not graduate but requires less data and effort to create a predictive outcome. CPS's work has been very influential and has been implemented in many states and school districts.

School mobility. The number of schools attended by a student has been found to be a strong indicator of a student's likelihood of dropping out. This study will refer to the number of schools attended as mobility. There are many potential reasons a student might change schools (e.g., family move for work, experiencing homelessness, changing which parent that the student is living with, or becoming a foster child). A change in school could result from an improvement in the student's life, or it could result from an adverse event. Rumberger and Larson (1998) suggest that school mobility is a symptom of student disengagement and a strong indicator of becoming a high school dropout. Their study found that students that were not mobile had an 8.3% rate of dropping out, where students with two or more school changes had a dropout rate of 23.3%. Dalton, Glennie, and Ingels (2009) looked at the correlation between school changes and dropping out of high school. They found that when counting school changes excepting those for promotion to a new school level, that students who experienced no school changes have a dropout rate of 4.0%, while those with four school changes had a dropout rate of 9.4% (Dalton, Glennie, & Ingels, 2009). Students in Los Angeles Unified who changed schools during middle school or high school were much more likely not to complete high school; the effect was most severe from middle school changes (Silver et al., 2008). Silver et al. (2018) found that students with high mobility had 0.52 odds of graduating, indicating they were about half as likely to graduate as students who did not experience high mobility.

School mobility has an impact not just on a mobile student's graduation outcome. It can also impact students who are not mobile but attend schools with high levels of student mobility. South, Haynie, and Bose (2007) document this phenomenon in their study, where they attribute the impact of student mobility on weak levels of school attachment and lower levels of student performance of entire schools. They suggest that mobility negatively impacts student's friendship networks and their involvement with their school. Students in their study with high mobility levels had lower course performance, were more likely to be depressed, were more likely to be immigrants, and were more likely to receive public assistance.

Retention and overage. Student retention in any grade was identified by Bowers (2010) to be highly predictive of whether a student would become a dropout. According to Roderick (1994), a student retained once was 69% predictive of becoming a dropout, and being retained two or more times than once was 94% predictive. Multiple studies have examined the connections between retention and graduation (Austin ISD, 1982; Bowers, 2010; Curtis, Macdonald, Doss, & Davis, 1983; Dalton et al., 2009; Eide & Showalter, 2001; Gleason & Dynarski, 2002; Hess, Alfred, & Lauber, 1985; Roderick, 1994)

Students who are overage compared to their grade-level peers are at high risk of dropping out of high school (Gleason & Dynarski, 2002; Kurlaender & Jackson, 2012; Roderick, 1994). A student becomes overage by being retained in lower grades or through course failure in secondary schools. To assess concerns about overage students and inform decisions, educational institutions have developed on-track indicators to allow schools to intervene (Mac Iver & Messel, 2013). Students in Los Angeles Unified who were over-age, greater than one year older than their ninth-grade peers, were found to be half as likely to graduate from high school. (Silver et al., 2008). Roderick (1994) found that students who were overage in the sixth grade showed signs of disengagement from high school primarily through increased absenteeism. These students had begun to show early signs of concern by the eighth grade. Roderick concluded that the data supported the hypothesis that being overage led to school disengagement and suggested these students were at risk of not graduating.

Demographics. Some demographic data have been connected to graduation, particularly membership in lower socioeconomic groups, and designation as an English language learner has been correlated to a higher risk of not graduating (Dalton, Glennie, & Ingels, 2009; McCaul, 1989; Suh & Suh, 2007). Although successful completion of high school varies when looked at by race and ethnicity, membership in particular groups has not been found to be a strong predictor of graduation when other factors are controlled (Nam, Rhodes, & Herriott, 1968; Robison, Jaggers, Rhodes, Blackmon, & Church, 2017). Being African-American, Latino, Native American, or male has been correlated to lower graduation rates. However, the effects were not a strong factor on their own when other factors were considered (Doss, 1986; Fram, Miller-Cribbs, & Van Horn, 2007; Robison et al., 2017; Stearns & Glennie, 2006). Gender has a small impact, with females being more likely to graduate than males (Phinney, 2016; Robison et al., 2017; Stearns & Glennie, 2006).

Combining indicators. Early warning indicators are much more successful when they are utilized in combination with multiple other indicators to complete a picture of a student's risks. Hammond et al. (2007) found that combinations of risk factors are most likely to result in consistent predictions. In an analysis of factors, Gleason and Dynarski (2002) found that using a single indicator was rarely useful in predicting dropouts. The most predictive factors were high absenteeism and being overage by two or more years for middle school students. The author's evidence indicates that combinations of multiple factors are much better at providing insight into potential graduation outcomes. Students with four predictors in middle school were the most likely to drop out. Using the same risk factor analysis for high school students had much higher levels of accurate prediction. The authors were very skeptical that use of risk factor indicators was enough to predict dropouts and caution that many students may be targeted for interventions inappropriately.

Other authors have also found that combinations of factors are better than individual indicators. Balfanz et al. (2007) found several other factors that predicted students would drop out: failure of math or English at the sixth grade, poor behavior, suspensions, and multiple class failures. Combinations of these indicators increased their predictive power. The indicator that Balfanz et al. (2007) found was strongest in isolation was chronic absenteeism. Mac Iver and Messel (2013) detailed the "ABCs" of being on track, which were attendance, behavior, and course performance in a study of students in Baltimore. They found that the most reliable predictors were 9^{th}-grade attendance, 9^{th}-grade course failure, and suspension of three days or more. The study also supported that being male or overage was also predictive of graduation outcome. They examined the same indicators both as an eighth-grade early warning and repeated in ninth-grade. The ninth-grade indicators were much stronger, suggesting that this year in particular, was an important year in determining the student's graduation outcome.

In a meta-analysis, Bowers et al. (2013) compared the effectiveness of 110 potential dropout indicators taken from 36 studies. It found that longitudinal growth models provided the highest accuracy and that the single most accurate individual indicator was low or failing grades. The authors argue that researchers have been too optimistic in their level of certainty in understanding who will drop out. While much research has been done in this area, the results are inconsistent. In this study, they produced a synthesis of factors from calculations across the 36 studies they analyzed. Bowers et al. (2013) strongly support the work of Balfanz et al. (2007), which researched six potential warning flags. A student found to have one flag gave a 64% chance of predicting if that student would drop out. With four flags, the prediction accuracy increased to 92%. Pagani et al. (2008) found that students with the combination of having three flags, in this case being retained, from a single-parent family, and having a mother with less than a high school diploma, had a 97% chance of dropping out.

The indicators from Bowers et al. (2013) were compared against the data available from the Oregon Department of Education to determine which would be the most useful in predicting a graduation outcome within five years of starting high school. The data groupings for the identified indicators are broken down in Table 2.

Table 2

Graduation Indicators

Indicator Group	Indicators and Supporting Literature
Attendance	Attendance (Balfanz et al., 2007; Ekstrom et al., 1986; Kupersmidt & Coie, 1990)
Behavior	Discipline (Ekstrom et al., 1986)
	Suspension (Balfanz et al., 2007; Ekstrom et al., 1986; Suh & Suh, 2007)
Demographics	English Learner (Dalton et al., 2009)
	Low-SES (Dalton et al., 2009; McCaul, 1989; Suh & Suh, 2007)
	Overage (Silver et al., 2008)
	Race (Doss, 1986; Fram et al., 2007; Robison et al., 2017)
Performance	Course Failure (Allensworth, 2013; Allensworth & Easton, 2007; Balfanz et al., 2007; Kupersmidt & Coie, 1990; Silver et al., 2008)
	9th Grade on-track (Allensworth, 2013; Allensworth & Easton, 2007; Dalton et al., 2009; Silver et al., 2008)
	Retention (Austin ISD, 1982; Bowers, 2010; Curtis et al., 1983; Dalton et al., 2009; Eide & Showalter, 2001; Gleason & Dynarski, 2002; Hess et al., 1985; Roderick, 1994)
Mobility	Schools attended (Dalton et al., 2009; Silver et al., 2008)

Note. Adapted from Bowers et al., 2013.

The indicators are separated into five groups: attendance, behavior, demographics, performance, and mobility.

Districts have attempted to utilize data to create early warning systems for potential dropouts. Allensworth (2013) gave an overview of how the Chicago Public Schools (CPS) established an early warning system, then utilized it to improve student success. School leaders recognized that knowing what the indicators of success are was not enough. They had to develop a system that allowed school leaders to turn challenges into actions that allowed for effective intervention. Once students were identified as at-risk, which was a process that was now well understood, leaders identified appropriate interventions to move the students toward success. CPS found this strategy to be a significant improvement for student outcomes. A critical finding of this research was that ninth-grade "on-track," GPA, or course failures each predict graduation with an 80% accuracy. The addition of test scores, mobility, race, economic status, and gender to the on-track indicator only improved accuracy by an additional 1% for a combined total of 81% accurate prediction. According to Allensworth (2013), the on-track factor alone is most important as an indicator. Increased absences correlated to decreases in school achievement, so absenteeism and engagement were essential areas for improvement. The study showed that by increasing attention and focus on actionable improvements in student absenteeism, grades, and other factors, on-track status improved in CPS from 56% in 2001 to 73% in 2011. This research points the way to the practical application of early warning indicators for increasing student graduation. Particularly interesting in this study was that demographic factors, including race and socioeconomic status, had little impact on student outcomes when results were controlled for on-track status.

Los Angeles Unified school district in the early 2000s was in a dropout crisis, with more than 50% of high school students not graduating on time. Silver et al. (2008) followed 48,561 9th grade students in Los Angeles through their high school career to their expected graduation to determine which factors related to high school graduation. One-third of the cohort failed to move on to tenth-grade on time or dropped out during their freshman year, emphasizing the importance of the ninth-grade as a pivotal year in school. The study found that the strongest negative demographic factors that predicted dropping out were being Latino, African American, male, an English learner, and overage (having been held back in lower grades). The strongest positive demographic factors that suggested completion of high school were female, White, Asian, not overage (never held back), and proficient in English. Academic experiences that increased a student's chance of graduating on time were passing algebra one by the end of the freshman year, achieving a proficient score on a state test, and attending a single high school. Experiences that increased the student's chance of becoming a dropout were: not passing algebra 1, two or more Fs in middle school, and attending more than one high school. A history of failing classes at the middle school was a troubling sign, notably if these failures continued through the 8th grade. High rates of student absences were shown to increase a student's chances of dropping out. Absences were a sign of disengagement from school.

Gap in Research of Virtual Schools and Graduation Rates

Distance learning has a history that goes back to at least the 1700s (Harting & Erthal, 2005). It began with paper-based correspondence courses where material and assignments were mailed back and forth between learners and their teachers. Over time, many different techniques and technologies were implemented, including the postal services, radio, television, and then computers with the internet. It was only in the 1990s when computers and the internet could offer fully online courses for students, first at the university level, then later deployed in the K-12 system. Harting and Erthal (2005) argue that deploying technology has been motivated by a desire to provide educational opportunities to those who cannot access them. While learning at a distance has a long history, attending school fully online has a much shorter history. Virtual schooling is new enough that there remain many gaps in our knowledge of what makes for a successful school.

While virtual schooling has grown dramatically, research of effective practices has not kept up (Arnesen et al., 2019; Barbour, 2010). A meta-analysis of online learning compared to other instruction methods found the amount of available research to be inadequate and often too specific to a particular teaching context, for example, studies by professors of their classes (Means et al., 2010). Their highest level of confidence came from evidence that online activities that pushed students to reflect on their learning led to improvements in their outcomes. Means et al. (2010) state that "…the field lacks a coherent body of linked studies that systematically test theory-based approaches in different contexts" (p. 49). Chingos (2013) argued that we know very little about virtual schools' effectiveness, particularly those using alternative methods for teaching.

Graduation rates are lower at virtual schools; however, the literature does not indicate a reason. Toppin and Toppin (2016) argue for the importance of online learning as an area of study; they report that based on trends as of 2015, virtual school enrollments have the potential to eclipse traditional student enrollments within ten years. Toppin and Toppin (2016) state that virtual academies' growth has outpaced researchers' ability to study them and establish best practices for effective virtual schools. Therefore, virtual school decision-making has become a matter of trial and error with insufficient insight from research. The COVID-19 pandemic in 2020 thrust nearly all schools into the experimentation of what might work without sufficient support and preparation, transforming a concern for virtual schools into a critical matter of urgency for all schools.

The rate of high school non-completers remains high and is a threat to the economic future of the dropouts and the state of Oregon (McCaul et al., 1992; Oregon Department of Education, 2018, 2020a; Zaff et al., 2017). The low performance of Oregon virtual schools on graduation measures is all the more frustrating in that the literature on distance learning methods shows that the means of delivery should not be a factor in determining the success of the student (Cavanaugh et al., 2004; Means et al., 2013, 2010). If the delivery method does not impact performance, there must be something else explaining the discrepancy that is apparent in virtual school performance.

Conceptual Framework

Several studies will be used to provide a conceptual framework for this study. Having written the most extensive and current study on graduation in Oregon, Phinney (2016) will be used as a model for analyzing risk factors for high school graduation. Phinney relies on two other studies as a framework which will also underpin this study. Attendance, behavior, and course performance (the ABCs) from Mac Iver and Messel (2013) and the conceptual model of student performance in high school by Rumberger and Lim (2008), illustrated in Figure 3, provide the overall frameworks of how to understand early warning indicators. The insight from these studies will allow this study to be designed in such a way as to examine what is already known about graduation and dropping out to determine what role, if any, the virtual school environment plays in this process.

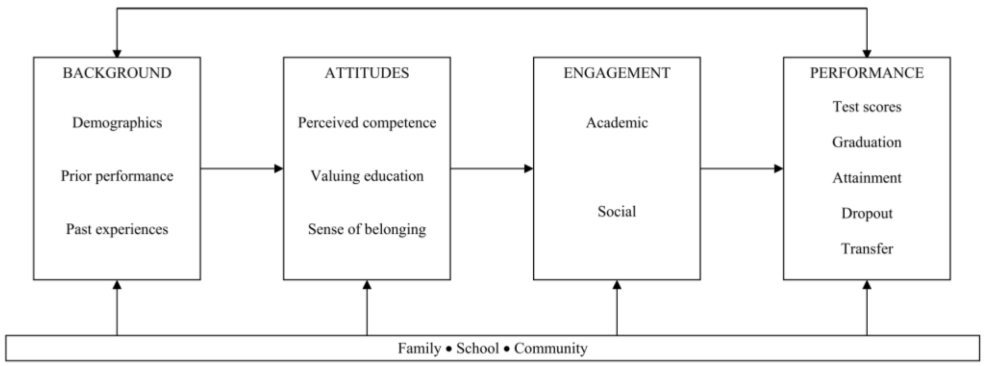

Figure 3. The Conceptual Model of Student Performance in High school from Rumberger and Lim (2008).

Not all elements in these frameworks can be analyzed in the planned study. The data that will be available will not cover all framework topics. However, a subset of variables taken within the design of the framework should offer useful insight. The final piece that will complete the theoretical framework is the analysis of Bowers et al. (2013), which listed the most researched indicators and compared each indicator's predictive value. This article is beneficial because it allows the study to focus on factors that are both accessible in the data and more predictive. This study will utilize the Balfanz et al. (2007) model that combined multiple factors, Bowers et al. (2013) found that Balfanz et al. had the most effective predictive model of many compared. In following the consensus that it is a combination of factors that is most insightful in the study of graduation attainment, the most useful data points can be collected to improve the accuracy of the analysis.

Indicators and Study Design

The indicators utilized for this study will be broken down into five categories: attendance, behavior, demographics, performance, and mobility. Many previous studies support how these categories and the specific indicators connect to graduation prediction. Attendance was connected by multiple authors (Balfanz et al., 2007; Ekstrom et al., 1986; Kupersmidt & Coie, 1990). Student behavior problems, including suspensions from school, have also been predictive (Balfanz et al., 2007; Ekstrom et al., 1986; Suh & Suh, 2007). Demographic data has also been connected to graduation, particularly membership in lower socioeconomic groups and designation as an English language learner (Dalton, Glennie, & Ingels, 2009; McCaul, 1989; Suh & Suh, 2007). Additional available data on demographics will also be available for descriptive purposes, including gender, racial group, and special education participation. Student retention is another factor that is connected to graduation (Austin ISD, 1982; Bowers, 2010; Curtis et al., 1983; Dalton et al., 2009; Eide & Showalter, 2001; Gleason & Dynarski, 2002; Hess et al., 1985; Roderick, 1994). Being over-age compared to same grade-level peers has also been connected to graduation (Silver et al., 2008). The social factor connected to graduation is student mobility, particularly connected to changing schools while not being promoted to a new level of schooling (Dalton et al., 2009; Silver et al., 2008)

Summary of Literature Review

The literature establishes several essential points as a basis for this study. The chapter started by placing graduation rates in a historical context and discussing life outcomes impacted by graduation or dropping out. It then discussed why some students might choose to escape from traditional schools to virtual schools and the different outcomes of the two types of schools. The review examined how graduation rates had been improved and the results specific to the state of Oregon. Finally, there was a review of different attempts to study graduation indicators and which strategies and indicators have been most useful in explaining which students were likely to graduate. There are no indicators in isolation that are certain predictors of graduation. There are some that are better than others, and there is some agreement on which factors are stronger. One theme that emerged in the literature is that combining multiple indicators into a model gave the most consistent predictive results. This study will build on this knowledge by attempting to illuminate virtual school as a potential graduation factor or determine if other previously studied indicators explain why students in Oregon virtual schools have experienced lower graduation rates than their traditional school peers.

Chapter 3: Methodology

The following chapter explains the methodology used to analyze data that may be predictive of student graduation within five years of starting high school for students attending virtual and traditional schools in Oregon. The study examined longitudinal data from the Oregon Department of Education that included student records on attendance, behavior, demographics, performance, social, and attendance at a virtual or traditional school. The study methodology is built on several researchers' work featured in the literature review (i.e., Bowers et al., 2013; Mac Iver & Messel, 2013; Phinney, 2016; Rumberger and Lim, 2008). By analyzing known predictive factors and assessing if participation in a virtual school was also a predictive factor, the impact of a student's choice to attend a virtual school was examined in the context of their five-year graduation outcome. Discussion of the research questions, the rationale for the methodology, data analysis, participants and setting, design and procedures, measures, and ethical considerations follow.

Purpose Statement & Research Questions

The purpose of this causal-comparative study was to compare graduation outcomes, defined as completing high school within five years, for students who learned online in Oregon virtual schools to students who attended traditional schools. To obtain an Oregon diploma and be defined as 'graduating,' students must accumulate 24 credits (Oregon Department of Education, n.d.). Student attendance data was utilized to determine what percentage of their school attendance was in a virtual school based on the student's average daily membership, an attendance measure that the state of Oregon uses for attendance, and records separately for each school attended.

This research study documented if there was a discrepancy between the graduation outcomes of Oregon’s virtual and non-virtual schools, as preliminary research suggested, by investigating the following research questions:

Research Question 1: When examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits?

Research Question 2: Do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates?

Research Question 3: What combination of indicators is most useful for predicting a virtual student’s graduation outcome?

Rationale for Methodology and Research Design

This quantitative study was performed using a causal-comparative methodology. The causal-comparative methodology is appropriate when two groups need to be compared, but a variable is different between the two groups (Mills & Gay, 2019). In this study, the dissimilar variable was the student's school setting, virtual or traditional. Utilizing this methodology, data that already existed were analyzed to explain relationships in the analyzed variables. The data contained the graduation outcomes of students who have concluded their K-12 education upon leaving school either as graduates or non-graduates. According to Brewer and Kuhn (2010), in a causal-comparative study, the following elements would be included:

- Investigate the cause and effect relationship between variables
- Not manipulating the variables because the events have already occurred
- Not creating groups of participants, the groups already exist
- Make group comparisons
- Studying two or more groups, and
- Focusing on the differences between groups

This study aimed to determine the effect of attending virtual school on the student's eventual graduation outcome. The causal-comparative research design fits the data and the research questions of this study (Brewer & Kuhn, 2010; Mills & Gay, 2019).

Participants and Setting

The data for this study were collected from existing databases that have the required data available. The Oregon Department of Education maintains data on all students who attended schools in Oregon. An agreement with the Oregon Department of education was negotiated to provide longitudinal data from their existing database for analysis in this study. The participants for this study were students who have recently left high school, both graduates and non-graduates. The students began high school during the 2013-14, 2014-15, and 2015-16 school years. Data were added into the database throughout the student's education with the final entry of data during

January of 2020 for students who completed or left school in these cohorts as of Spring 2019.

Students who have attended virtual and traditional schools were represented in the study. Each student's graduation outcome was compared to their predicted outcome based on factors that have been identified in the literature that inform how likely a student was to graduate. The student's status as a virtual or traditional student was analyzed to determine if the schooling model's choice influenced the graduation outcome. The data were collected in the form of exported spreadsheets from the existing database. It was then analyzed using SPSS. In total, four-year graduation outcomes were available for 137,637 students in the target cohorts. Five-year graduation outcomes were available for 91,849 students.

Table 3 presents the cohort participants available by year and graduation outcome.

Table 3

Students with Graduation Outcomes by Cohort Year

High School Start	Four-year Outcomes	Five-year Outcomes
2013-2014	45,980	45,980
2014-2015	45,869	45,869
2015-2016	45,788	
Total	137,637	91,849

The three cohorts included all Oregon students who began high school in each of the three cohort school years. This large data set was desirable to improve the generalizability of the study. This study used the entire population of students who were in the selected cohorts.

Design and Procedures

The data provided for this study came in a series of comma-separated-value (CSV) files that were imported into Microsoft Excel for cleaning and final assembly of the dataset. Each row of data had a unique student identifier used to track students by the Oregon Department of Education. This unique identifier allowed the data from multiple sheets to be combined, cleaned, and transformed to prepare for analysis in SPSS. The process of preparing these data was a significant undertaking. Once the data were delivered, preparing them for analysis was the most time-consuming element of the study.

The outcome and predictor indicators were based on the work of Balfanz et al. (2007) and with additional variables drawn from Bowers et al. (2013). The following data were requested from the Oregon Department of Education.

Outcome variable.

1. Graduation outcome, defined as completion of 24 units to receive a diploma (categorical)
    a. Graduated within 4-years/Did not graduate
    b. Graduated within 5-years/Did not graduate

Predictor variables.

1. Attendance, Behaviors, Performance (ABCs) :

a. Attendance: Average daily membership, a record of attendance for each school year maintained by the state of Oregon (numerical)

b. Behavior: Student history of behavior incidents

    i. Out of school suspensions (in days)

    ii. In-school suspensions (in days)

    iii. Expulsions (in days)

c. Performance: 9^{th}-grade on track (nominal)

2. Demographic:

    a. High school entry cohort (categorical)

        i. 2013-14

        ii. 2014-15

        iii. 2015-16

    b. The student had an Individual Education Plan (IEP) (categorical)

    c. The student had a 504 Plan (categorical)

    d. The student was a designated English language learner (categorical)

    e. Gender (categorical)

    f. Ethnic group (categorical)

    g. Socioeconomic status/Free and reduced lunch (categorical) – Reported as an entire school if the school or district met a specified percentage (categorical)

    h. Identified as “Talented and Gifted” (TAG) (categorical)

    i. Birthdate (date)

i. Computed age start at 9th grade (scale)

j. Retention (nominal)

3. Mobility

a. Count of schools attended (scale)

Additional predictor variable.

4. School Setting

a. The computed ratio of school days the student attended in a virtual school out of total Oregon enrollment (scale)

Processing Data and Assembling the Final Dataset

Data were downloaded in multiple files Comma Separated Value files (CSV) by topic: 9th Grade on Track, Average Daily Membership (attendance), graduation outcomes, and Limited English Proficiency (LEP) program participation. Individual student records were attached to an SSID (Secure Student Identification Number), which allowed student records from multiple sources to be compared and combined.

The first step in preparing the dataset was to assemble a list of students for the final analysis. The raw data files from ODE contained many records for students without graduation outcomes who were not usable for this study. A master key index was created in a spreadsheet with all SSIDs for students with a graduation outcome. This list was then sorted, and duplicates were removed. A key index was created to filter all CSV files for data connected to students with a graduation outcome. After the individual sheets were filtered, the process of combining the data started.

Missing Data and Reduction in Dataset

Some data fields were missing or incomplete for some students. The missing data that were most important for this project were the Average Daily Membership (ADM) data. In some cases, students with a graduation outcome had no corresponding attendance data available. The concern with missing ADM data was that it was used to establish which type of school a student had attended, for how long, and for calculating measures including attendance and mobility. Some students had ADM data that showed very minimal enrolled days at Oregon schools. For this study, it needed to be known how long and what type of school a student had attended. Therefore, students with no or limited ADM data were removed from the analysis. Students whose enrollment records totaled less than 360 days were removed from the dataset. The final student list was reduced to 130,901 for four-year outcomes. The five-year participants were reduced to 87,291. The final cases available for analysis are shown in Table 4.

Table 4

Students with Graduation Outcome by Cohort Year with Unused Cases Removed

High School Start	Four-Year	Five-Year	Expected Graduation
2013-2014	43,656	43,656	2017
2014-2015	43,635	43,635	2018
2015-2016	43,610		2019
Total	130,901	87,291	

Final Dataset Variables

After cleaning and combining data, the following indicators were available for analysis, as shown in Table 5. Variables that were not used were excluded upon being analyzed for their univariate predictive ability to the outcome variables.

Table 5

Outcome and Predictor Variables Available for Analysis

Category	Indicator	Not Used	Description of Variable or Reason Not Used
Outcome	Graduated in 4 years		The student graduated within four years by completing 24 credits
	Graduated in 5 years		The student graduated within five years by completing 24 credits
ABCs	Attendance		The ratio of Days present divided by days enrolled
	Behavior		Behavior days (suspended, expelled, etc.) divided by days enrolled
	9th grade on track		The student had a minimum of six credits by the end of their 9th-grade year
Demographic	Age at start of high school		How old was the student when they started high school?
	Ethnicity	X	Low contribution to the model
	Gender	X	Low contribution to the model
	Economically Disadvantaged	X	Low contribution to the model
	Retained during K-8		Student ever retained between kindergarten and 8th Grade
Program	504	X	Low contribution to the model
	Indian education	X	Low contribution to the model
	Individual education plan	X	Low contribution to the model
	English language learner	X	Low contribution to the model
	Special education		Was the student in a special education program?
	Talented and gifted		Was the student identified as talented and gifted?
	Virtual school days out of total enrollment		The ratio of days attended at a virtual school divided by days enrolled in any Oregon School
Mobility	School Count		Count of all schools attended in PK-12

Enrollment Grouping

This study's focus was to examine how graduation outcomes may be different for virtual and traditional high school students and to explore what might explain any differences found. One of the major difficulties inherent in this problem was which students were considered virtual students, compared to those that were not virtual. For this study, to compare various virtual student groups, students were divided into five enrollment groups based on their school attendance. Students who had only attended a traditional school were labeled “traditional” this group was the largest, with over 90% of Oregon students. The remaining students were grouped based on the ratio of days they had attended a virtual school compared to their total enrolled days in Oregon. They were placed in non-overlapping groups at equal ratios (i.e., $> 0 \leq .25$, $> .25 \leq .50$, $> .50 \leq .75$, and $>.75$). The grouping allowed for several different analysis options when assessing groups: All students, an individual group, and any virtual.

Ethical Considerations

The Institutional Review Board granted permission to conduct this research study on August 31, 2020.

The Oregon Department of education data contained confidential information and data that allow for identifying individual students. It was, therefore, critical that data were handled carefully. Furthermore, this study had to meet the University of Portland Institutional Review Board requirements and those of the Oregon Department of Education. Several procedures were implemented to ensure confidentiality of student data:

- Data were stored within the secure University of Portland network and could not be moved to any device not on the University network or onto a portable device like a USB drive, hard drive, or printed copies.
- Data were accessed from a dedicated computer in a locked home office. The computer was only used for this project. This computer had a password to protect it from unauthorized entry by anyone other than me. The computer automatically locked itself after 15 minutes of being inactive.
- Output data from the analysis did not have any personally identifiable information and was only shown in aggregate group forms that make the identification of any student impossible.
- The Oregon Department of Education must approve any data or analysis from the project before publication.

Due to the procedures required for data handling, it was not anticipated that there would be any potential harm to participants.

Data Analysis and Model Interpretation

The study used logistic regression to analyze if virtual schooling was a predictive indicator that had a strong or weak connection to the outcome variable. Field (2013) explained logistic regression as the process by which a researcher tried to predict the outcome of a categorical variable. In this case, there are three possible graduation outcomes: graduated in four years, graduated in five years, and did not graduate. Because logistic regression was used with a binary dependent variable, the model was run twice using graduated within four years or not and graduation within five years or not. Both continuous and categorical indicators can be used as independent variables to predict logistic regression outcomes (Muijs, 2011). The data for this study conformed to these types of variables. Many studies have investigated graduation outcomes utilizing logistic regression (e.g., Fernández-Suárez, Herrero, Pérez, Juarros-Basterretxea, & Rodríguez-Díaz, 2016; Franklin & Trouard, 2016; Kemper, Vorhoff, & Wigger, 2020; Phinney, 2016; Schnase, 2011).

Data must meet four assumptions to perform a logistic regression (Laerd Statistics, n.d.).

1. The dependent variable must have a dichotomous value (i.e., “0” or “1”).
2. There are one or more independent variables that were continuous or categorical.
3. Independent and dependent variables were mutually exclusive.
4. There was a linear relationship between any continuous variables and the dependent variable tested in SPSS using the Box-Tidwell procedure to compare the continuous variables against a log of themselves (Box & Tidwell, 1962).

For assumption four, if the comparison results in $p > .05$, then the assumption would be thought to be valid. Unfortunately, large data sets cause the Box-Tidwell test to fail because nearly all initial variables will be $p < .001$, in the same way, that the Hosmer and Lemeshow test fails with large datasets (Wuensch, 2014).

In linear regression, there is an assumption that the outcome variable has a linear relationship to the predicting variables. However, when outcome data are categorical, they violate linear regression assumptions (Field, 2013). Therefore, a different method of regression must be used. Logistic regression changes the data using logarithmic transformation to make the analysis work by showing a non-linear analysis that appears linear. The result of logistic regression analysis is not a direct value of the outcome variable. Instead, the analysis predicts the probability of an outcome based on the predictive variables. The formula for logistic regression is shown in the following formula adapted from Field (2013):

$$P(Y) = \frac{1}{1 + e^{-(b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots + b_n X_n)}}$$

In the formula, *P(Y)* represents the probability of the outcome. A value close to 1 means the outcome was very likely to occur, and a value close to 0 indicates the result is not very likely to occur. When several predictive variables are present, they are represented by (X_S) in the formula.

Several statistics generated in logistic regression analysis are useful for assessing the model and its constituent variables (Field, 2013; Muijs, 2011). The log-likelihood statistic evaluates if the model was a good fit. Log-likelihood is a summation of the actual and predicted outcomes of the model. It calculates how much of the model outcome was not explained by the predictive variables. A higher value of the log-likelihood statistic represents a worse outcome for the model's success since it shows the portion of the result not explained in the predictive variables (Field, 2013). An additional element in explaining the components of the model is the Wald statistic Z^2. Wald calculations can be used to help explain the comparative impact that different indicators have had on the results of the model. A higher number indicates more impact (Field, 2013)

The most important statistic for understanding a logistic regression model is the odds ratio. This ratio is represented in SPSS as Exp (B). An increase in the odds ratio explains how an increase in the value of an independent variable influences the increased likelihood of the dependent variable's outcome. A value of one indicates no impact. Less than one shows the independent variable has a negative relationship to the dependent variable outcome. A higher value than one indicates that for each unit of increase of the independent variable, the dependent variable has a corresponding increase. A result that is much greater than one indicates a strong relationship (Muijs, 2011).

$$\text{Odds ratio} = \frac{\text{Odds after a unit of change in the predictor variable}}{\text{Original odds}}$$

Sensitivity represents the model’s ability to predict true positives correctly; a number at one or 100% represents perfect prediction. Likewise, specificity represents the model’s ability to predict true negatives accurately; a number at 1 or 100% represents perfect prediction. Higher numbers for both indicate a better model. Precision demonstrates that the results would be consistently measured the same way upon repeated measures. Accuracy represents the total of all cases that were identified correctly as either negative or positive predictions. A higher number indicates a better model (Bowers et al., 2013; Goss-Sampson, 2018).

An essential step in performing a logistic regression is checking for inter-correlations and multi-collinearity in the indicators being used for the analysis (Pennsylvania State University, 2018). SPSS does not have a method for automatically calculating inter-correlations and multi-collinearity in its logistic regression procedure. The workaround uses the same dependent variable and independent variables but uses a linear regression analysis in SPSS. The correct figures can be selected in the linear regression dialog to generate inter-correlation, Variation Inflation Factor (VIF), and tolerance. The other information from the linear regression output is not utilized (Field, 2013). The VIF measurement is used to decide if the indicators are measuring the same thing or something different. A VIF at one indicates that there is no correlation between the factors used in the analysis. A VIF that is higher than four needs investigation. A VIF result that is higher than 10 indicates a serious concern that there is multicollinearity between the indicators. Tolerance, which is reported with VIF, is a related calculation that is the reciprocal of VIF. Tolerance measurements below 0.2 require investigation and may indicate multi-collinearity. (Miles, 2014).

A goodness of fit test indicates how predictive a model is of what the model is attempting to explain. Multiple pseudo R^2 tests are in this category (UCLA Statistical Consulting Group, 2011). The values cannot be compared against models that utilize different datasets. However, for the same data, a pseudo R^2 value can indicate which model best fits the data analyzed. The most common pseudo R^2 tests used in logistic regression are Cox and Snell R^2 and Nagelkerke R^2. As these measures approach one, they indicate a perfect predictive outcome. One problem with Cox and Snell R^2 is that the value cannot reach one because of its calculation method. Nagelkerke R^2 modified the approach to the measure used in Cox & Snell $R^{2,}$ making it possible to reach a value of one. Since Nagelkerke R^2 can reach one, it can be described as predicting a percent of the model explained by the variables in the model; however, it is often confused in its interpretation with R^2 from linear regression but is not the same thing. The danger is that a pseudo R squared value like Cox and Snell R^2 or Nagelkerke R^2 may be perceived as having more weight than it deserves in the analysis of logistic regression. A pseudo R^2 is useful for comparing how the addition of variables improves a model utilizing the same dataset (Field, 2013; Hosmer, Lemeshow, & Sturdivant, 2013). Hosmer-Lemeshow R^2 (Hosmer et al., 2013) is also used to test the goodness of fit of a model. For the model to pass, the test needs to show a $p > .05$ to be significant. However, there is a known problem with this test. It is only useable for small datasets. For large datasets, this test fails, and it loses its ability to explain the goodness of fit (Wuensch, 2014). Therefore, this study's analyses focused on Cox and Snell R^2 or Nagelkerke R^2 to determine goodness of fit.

The last stage in creating a logistic regression model is establishing the final multivariate model (see Field, 2013; Muijs, 2011). There are two main methods of arriving at the final model. In the first method, each indicator is examined individually to test for significance against the dependent variable. After each is tested, those without significance are removed, then added in one at a time to see if they become significant when combined with the other independent variables. If they are found not to be significant, they are excluded. Part of the decision-making process in model building is the choice of what to include and what not to include. These decisions are guided by the literature, but decisions in any particular study have an impact on the outcome of the final model. The second method of arriving at a model involves using statistical software to complete a process to determine the best model for the given data. One example of this model used in this study is the forward stepwise method. The statistical software measures each indicator and then adds in additional indicators until the best model is determined; the software excludes indicators that do not add to the model.

Validity, Reliability, and Generalizability

In quantitative research, validity determines whether measurements measure what the study intends or claims to be measuring (Muijs, 2011). There is strong support in the literature for the measures that were investigated in this study. The measure for which there is not broad support in literature is the impact of virtual schooling on the likelihood of graduation. The validity of the data supplied by the Oregon Department of Education is supported by a comprehensive program of guidelines and training provided to the districts that provided the data (Oregon Department of Education, 2016).

Reliability in quantitative research refers to the level of error in measurements (Muijs, 2011). All measurements have some inherent errors. Using ex post facto data from student records makes it impossible to determine if all records are accurate. However, the records are from school district reports with specific criteria that have been issued by the state of Oregon (Oregon Department of Education, 2016). The consistency of the reporting requirements is a contributor to the reduction in potential errors.

A desirable goal of quantitative research is to generalize the study results beyond the sample under investigation. If a study is 'generalizable,' it suggests that results may be applicable to a larger population than the sample (Muijs, 2011). This study's sample size is the population of students who began high school in Oregon during 2013-14, 2014-15, and 2015-16 cohorts. The total number of the sample includes 137,637 students. After students with incomplete data were eliminated, the total sample was reduced to 130,901. Of this total, 12,866 participants had been enrolled in a virtual setting at some time during their education. The large sample suggests that the analysis will be generalizable beyond Oregon virtual schools and offer insight more broadly to virtual schools in the United States. Using a large sample size reduces the probability of either Type I or Type II errors (Muijs, 2011).

Summary of Methodology Chapter

This chapter discussed the methodology that was used to analyze longitudinal student data for students in the state of Oregon. The study investigated the relationship between virtual and traditional school settings and five-year high school graduation outcomes. Participants included students who were part of 2013-14, 2014-15, and 2015-16, 9th-grade cohorts. The analysis examined the students' graduation outcomes in terms of previously researched graduation predictors to determine if there were differences between virtual and traditional students. Chapter 4 will discuss the results of the analysis.

Chapter 4: Results

The purpose of this causal-comparative study was to compare graduation outcomes, defined as completing high school within five years, for students who learned online in Oregon virtual schools to students who attended traditional schools. The analysis in this chapter used descriptive statistics to explore the data and logistic regression to compare outcomes of students who attended virtual and traditional schools. In the previous chapter, the research methodology used in this study was described, including the source of data, how indicators were calculated, how the participants were selected, and how logistic regression would be used to analyze the dichotomous outcome. The report of the results is organized in the following way:

1. Demographics and descriptive analysis are explored for the participants, and the overall graduation outcome performance of the participants as a whole group is detailed.
2. Research Question 1: When examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits?
3. Research Question 2: Do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates?

4. Research Question 3: What combination of indicators is most useful for predicting a virtual student's graduation outcome?

The chapter concludes with a summary of the results.

Demographics and Descriptive Statistics

The gender composition of each enrollment group is shown in Table 6.

Table 6

Enrollment Group Gender and Percent Comparing Traditional and Virtual

			Virtual							
	Traditional		> 0 ≤ .25		> .25 ≤ .5		> .5 ≤ .75		> .75 ≤ 1	
Gender	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
Female	56,403	47.8	5,404	54.7	1,030	54.1	286	54.0	277	51.3
Male	61,595	52.2	4,479	45.3	873	45.9	244	46.0	263	48.7

The proportion of females is noticeably higher in all virtual groups as compared to the traditional groups. The group with the closest parity between genders were the students that spent the most time in a virtual setting.

The ethnic composition of the enrollment groups and each group's total size are shown in Table 7 and Figure 4. Notably, the group sizes are substantially different, with the largest group attending school in a traditional setting.

Table 7

Detailed Ethnicity by Enrollment Group

	Traditional		Virtual							
			> 0 ≤ .25		> .25 ≤ .5		> .5 ≤ .75		> .75 ≤ 1	
Ethnicity	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
American Indian or Alaska Native	1,872	1.6	222	2.2	26	1.4	9	1.7	3	0.6
Asian	5,150	4.4	113	1.1	37	1.9	9	1.7	13	2.4
Black or African American	2,967	2.5	178	1.8	18	0.9	6	1.1	11	2.0
Hawaiian or Pacific Islander	818	0.7	23	0.2	2	0.1	0	0.0	3	0.6
Hispanic or Latino	26,197	22.2	1,275	12.9	329	17.3	56	10.6	45	8.3
Multi-Ethnic	6,634	5.6	635	6.4	104	5.5	29	5.5	20	3.7
Ethnicity Other	35	0.0	5	0.1	0	0.0	0	0.0	1	0.2
White	74,339	63.0	7,432	75.2	1,386	72.9	420	79.4	444	82.2
Total	118,012	90.2	9,883	7.6	1,902	1.5	529	0.4	540	0.4

Of the virtual enrollment groups, students with the least time in a virtual setting (*n* = 9,883) dwarf the other virtual groups with a combined total of 2,971 between them. All enrollment groups show diversity in their student populations, while virtual school enrollment groups have a higher proportion of White students represented by their participation rates.

Figure 4 visualizes the data from Table 7, which shows ethnic distributions of each of the five enrollment groups.

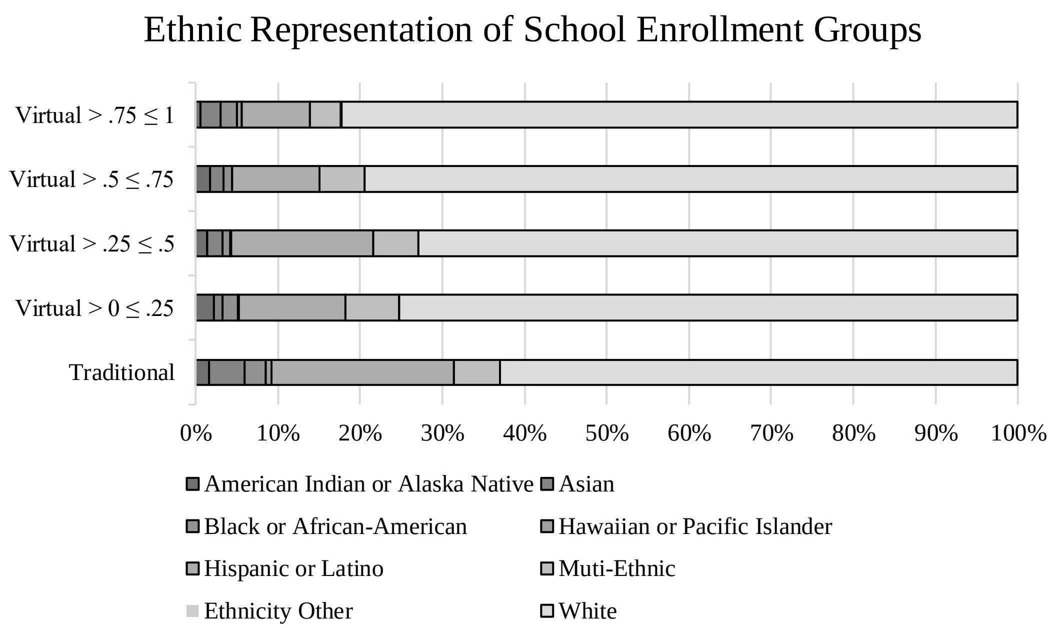

Figure 4. Ethnic representation of school enrollment groups by percent.

While there are diverse students represented in all enrollment groups, the figure shows that White students have a higher representation in the enrollment groups with the highest ratio of days attended in a virtual setting. The traditional group has the highest representation of non-White students.

The graduation data represented in Table 8 show that successive cohorts are improving their graduation attainment.

Table 8

High School Start Cohort Four-Year and Five-Year Graduation Rates

	Four-Year				Five-year			
	Yes		No		Yes		No	
High School Start	*n*	%	*n*	%	*n*	%	*n*	%
2013-2014	34,197	78.3	9,459	21.7	35,538	81.4	8,118	18.6
2014-2015	35,043	80.3	8,592	19.7	36,199	83.0	7,436	17.0
2015-2016[a]	35,775	82.0	7,835	18.0				

[a]Five-year graduation data were not available for this cohort.

In the 2013-2014 and 2014-2015 cohorts, the difference between four-year and five-year results improved by 3.1%, and 2.7% increases in positive graduation outcomes were seen after the fifth year of high school. The comparable rates for the national four-year graduation cohorts of the 2013-2014 and 2014-2015 cohorts were 84.6% and 85.3% (National Center for Education Statistics, 2018b, 2019a), with Oregon lagging at 78.3% and 80.3% for the same four-year statistic. An important positive point for Oregon and the nation is that rates are not stagnant and are improving each year, with Oregon rates behind but catching up to the national rate.

Tables 9 and 10 detail which groups of students were able to graduate disaggregated by demographic groupings.

Table 9

Four-Year Graduate and Non-Graduate Comparison by Demographic Group

		Graduated			
		Yes		No	
Variable	Category	*n*	%	*n*	%
All Students		105,015	80.2	25,866	19.8
Age at start of High School					
	≤ 14	9,917	84.0	1890	16.0
	> 14 ≤ 15	89,695	81.1	20,896	18.9
	> 15 ≤ 16	5,249	64.3	2,919	35.7
	> 16 ≤ 17	130	47.8	142	52.2
	> 17	24	38.1	39	61.9
Economically disadvantaged		36,240	76.5	11,163	23.5
Ethnicity					
	American Indian or Alaska Native	1,403	65.8	729	34.2
	Asian	4,919	92.4	403	7.6
	Black or African American	2,273	71.5	907	28.5
	Hawaiian or Pacific Islander	667	78.8	179	21.2
	Hispanic or Latino	21,422	76.8	6,480	23.2
	Multi-Ethnic	5,916	79.7	1,506	20.3
	Other	33	80.5	8	19.5
	White	68,382	81.4	15,639	18.6
Gender[b]					
	Male	52,074	77.2	15,380	22.8
	Female	52,922	83.5	10,478	16.5

[a]Economically disadvantaged includes students designated as disadvantaged and all students that attended schools classified as disadvantaged.

[b]Students listed as gender-neutral or other were not included due to small *n*, which may impact maintaining their privacy.

Students who started high school before 15 years old had a similar graduation rate to what all students achieved. However, a student who was over 15 when they began high school was much more likely not to graduate. Students designated as economically disadvantaged or attended schools designated as economically disadvantaged had a four-year graduation rate that was 3.7% lower than the rest of Oregon. However, as seen in Table 10, the spread on the five-year rate was lower at 2.5% less than the full population rate.

The results for ethnic groups show very different results for Oregon students when disaggregated. Many ethnic groups performed near the average, while several groups had notably different outcomes. Asian students in both tables graduated at much higher levels than other ethnic groups. Black/African American students struggled with a four-year graduation rate that was 8.7% lower than the whole state average. However, in the five-year analysis in Table 10, the spread was only 7.1% lower. The ethnic group that had the greatest struggle was the American Indian or Alaska Native cohort. In the four-year analysis, 65.8% graduated. In the five-year analysis, 67.9% completed high school. The spread between this group and the comparison state average was 14.4% and 14.3% in the two different analyses. Other groups saw a greater decrease in their spreads or could be said to be catching up.

Table 10

Five-Year Graduate and Non-Graduate Comparison by Demographic

		Graduated			
		Yes		No	
Variable	Category	*n*	%	*n*	%
All Students		71,737	82.2	15,554	17.8
Age at start of High School					
	≤ 14	6,825	86.1	1,101	13.9
	> 14 ≤ 15	61,110	83.0	12,499	17.0
	> 15 ≤ 16	3,678	66.6	1,842	33.4
	> 16 ≤ 17	106	56.1	83	43.9
	> 17	15	34.1	29	65.9
Economically disadvantaged[a]		26,080	79.7	6,637	20.3
Ethnicity					
	American Indian or Alaska Native	994	67.9	470	32.1
	Asian	3,316	93.8	219	6.2
	Black or African American	1,619	75.1	537	24.9
	Hawaiian or Pacific Islander	452	79.2	119	20.8
	Hispanic or Latino	14,560	79.5	3,758	20.5
	Multi-Ethnic	3,954	81.9	873	18.1
	Other	25	83.3	5	16.7
	White	46,817	83.1	9,538	16.9
Gender[b]					
	Male	35,784	79.5	9,230	20.5
	Female	35,953	85.1	6,303	14.9

[a]Economically disadvantaged includes students designated as disadvantaged and all students that attended schools classified as disadvantaged.

[b]Students listed as gender-neutral or other were not included due to small *n*, which may impact maintaining their privacy.

The analysis of gender results in Tables 9 and 10 tells another story of disparity in outcome. Female students graduated with a success rate of 83.5% compared to the male rate at 77.2%, a 6.3% difference in the four-year analysis. In the five-year analysis, the gap decreased to 5.6%.

The age a student was when they began 9th grade shows a large difference in whether they were able to complete their high school diploma; this impact was seen in the all-student analyses in Tables 9 and 10. Suggesting that students who had been held back prior to high school are at high risk of not graduating. The graduation rate for student disaggregated by age at the start of 9th grade and by enrollment group is shown in Figure 5.

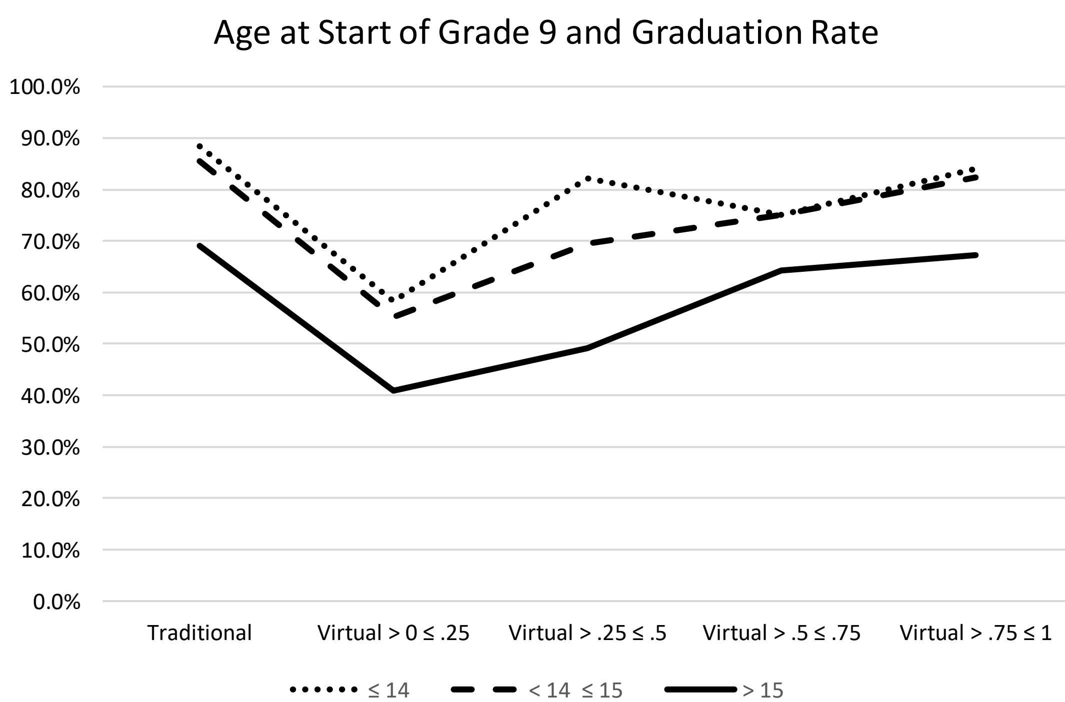

Figure 5. Graduation rate by age at the start of high school disaggregated by enrolment group.

Figure 5 showed several vital details. First, the group of students who started high school after their 15th birthday, classified as overage, had a much lower graduation rate than students who began high school before their 15th birthday. This pattern holds for students who attended virtual and traditional schools. The figure also visualizes that of students who have attended virtual schools, the students with the most days attended in virtual schools had the closest graduation outcome to traditional students.

In Tables 11 and 12, the graduation rates are detailed by program participation. These programs show both successes and challenges for participating students. Students with IEPs, 504 plans, and participants in English learner programs and migrant education performed slightly lower than the state's mean.

Table 11

Four-Year Graduate and Non-Graduate Comparison by Program Participation

	Graduated			
	Yes		No	
Variable	*n*	%	*n*	%
All Students	105,015	80.2	25,866	19.8
Had IEP	13,283	78.6	3,606	21.4
Had 504 plan	1,811	80.8	429	19.2
Indian education	1,295	71.1	527	28.9
Limited English Proficient[a]	18,653	78.3	5,180	21.7
Migrant education	2,284	78.7	618	21.3
Special education	10,215	62.1	6247	37.9
Talented and gifted	8,115	95.3	399	4.7

[a]Includes any student that had ever been designated LEP, including exited students.

The education program with the highest graduation rate was that of students who were designated as talented and gifted. These students graduated at 95.3% in the four-year analysis, with a slight increase to 95.7% in the five-year analysis.

There were two programs represented in Tables 11 and 12 with a considerable divergence from the full state mean for all students: Indian education, and Special education. Students who were designated as special education were the least likely to complete a high school diploma. It is notable that while this group has overlap with students who have IEPs, the results are very different, with the IEP figure approaching the state mean, while the special education designation was 18.1% lower than the state mean. All students who were designated as special education, have IEPs but many students with an IEP will not get a special education designation. They may be receiving speech, occupational therapy, resource, or other services that require an IEP.

Table 12

Five-Year Graduate and Non-Graduate Comparison by Program Participation

	Graduated			
	Yes		No	
Variable	*n*	%	*n*	%
All Students	71,737	82.2	15,554	17.8
Had IEP	9,923	80.5	2,405	19.5
Had 504 plan	268	76.6	82	23.4
Indian education	855	72.9	318	27.1
Limited English Proficient[a]	11,464	80.4	2,796	19.6
Migrant education	1,546	80.9	366	19.1
Special education	7,315	66.6	3,668	33.4
Talented and gifted	5,439	95.7	247	4.3

[a]Includes any student that had ever been designated LEP, including exited students.

One unexpected figure from the program analysis was the Indian education program. Students in this program were graduating at a higher rate than students who were ethnically identified as Native Americans or Alaska Natives in Tables 8 and 9. Notably, there were more students in the Indian education program than there were ethnically identified as Native American, which suggests that a portion of those students are represented in a different ethnic category, most likely in the multi-ethnic designation.

Research Question 1

Research Question 1: When examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits?

When graduation rates are disambiguated by enrollment groups, which are traditional schools and varying amounts of virtual school participation, students have widely different outcomes. Table 13 shows four-year and five-year graduation rates by frequency count and percent.

Table 13

Graduation Rate by Traditional School and Virtual School Enrollment Group

	Graduated							
	Four-Year				Five-year			
	Yes		No		Yes		No	
	n	%	*n*	%	*n*	%	*n*	%
Traditional School	97,933	83.0	20,103	17.0	66,849	84.7	12,067	15.3
Virtual > 0 ≤ .25	5,069	51.3	4,821	48.7	3,498	54.3	2,940	45.7
Virtual > .25 ≤ .5	1,236	64.8	670	35.2	855	68.8	387	31.2
Virtual > .5 ≤ .75	372	70.2	158	29.8	259	73.8	92	26.2
Virtual > .75 ≤ 1	405	75.0	135	25.0	276	80.2	68	19.8

Table 13 shows that students who attended entirely traditional schools had the highest graduation outcome at 83% in the four-year analysis and 84.7% in the five-year analysis. Students who had the highest ratio of days in a virtual setting attained the next highest graduation rate. Students who spent 75% or more of their time in a virtual environment achieved a four-year graduation rate of 75.0%, 8.0% less than their traditional school peers, and 80.2% graduation in the five-year analysis, 4.5% behind their traditional peers. When examining these results with only the students who experienced at least a portion of their education in a virtual school, students with more time in a virtual school had much better performance than those with less.

Students with some virtual school experience, but with less than 25% of their school attendance in a virtual setting, were about as likely to graduate in four years as they were not to graduate, with only a slight improvement in the five-year analysis. To examine further the differences in the enrollment groups, Table 14 details the mobility of students by enrollment groups. Student attendance records were reviewed, and a count was made of each school that a student attended.

Table 14

Mobility of Students by Traditional School and Virtual School Enrollment Group

	n	Mean Schools Attended	*SD*
Traditional	118,035	5.35	2.466
Virtual > 0 ≤ .25	9,890	7.73	2.947
Virtual > .25 ≤ .5	1,906	6.03	2.375
Virtual > .5 ≤ .75	530	5.11	2.148
Virtual > .75 ≤ 1	540	3.08	1.517
Total	130,901	5.53	2.584

All Oregon students had a mean number of schools attended of 5.53, with traditional students slightly lower at 5.35. Students who had attended the most virtual school had the lowest mean school count of any group. Similarly, the group with the highest mean school count of 7.73 was the same group with the lowest positive graduation outcomes from Table 13. The differences in these groups were further illustrated by the visual presentation of data from Table 14 in Figure 6, where the contrast in school mobility can be seen clearly.

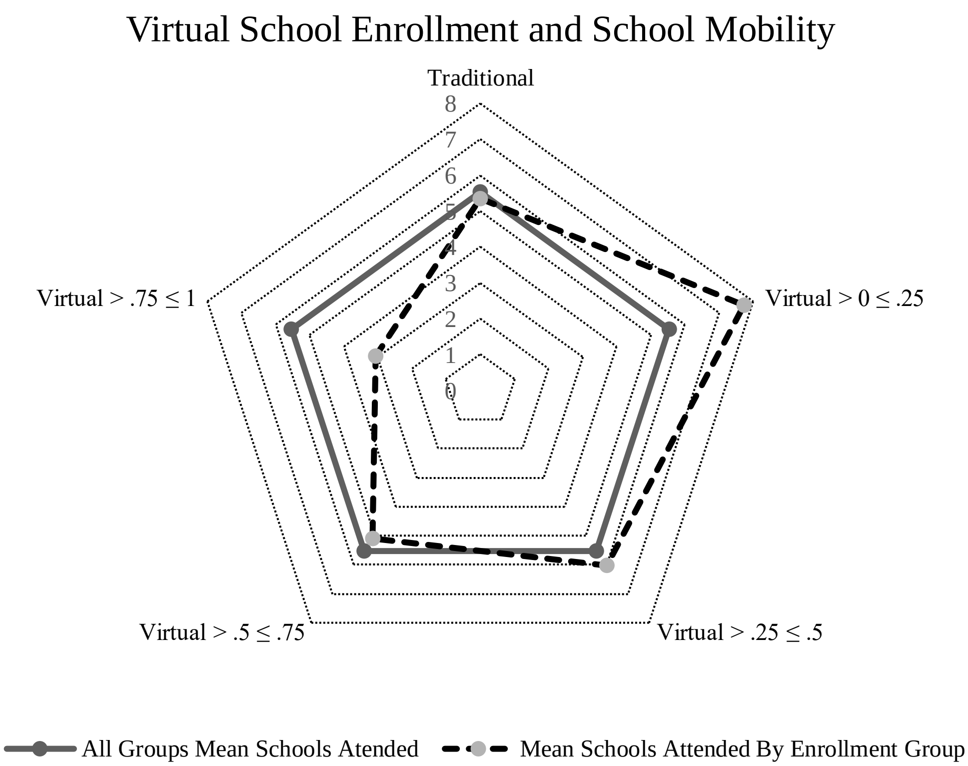

Figure 6. School mobility comparison for different enrollment groups.

Students who spent the most time in virtual schools had the least school mobility of any enrollment group shown in Figure 6. However, it is essential to note that the traditional school model includes students attending an elementary, a middle, and a high school that are counted as separate entities even in the same district. Virtual schools have adopted other models of organizing their school with adoptions of single schools for kindergarten through eighth-grade, in other cases, a single school for kindergarten through 12th grade. This distinction would tend to decrease school counts for virtual school attendees. The correlation of greater school mobility, a higher school count, and a lower graduation rate is suggested by the Virtual > 0 ≤ .25 enrolment groups distinction of having the lowest graduation rate and the highest mean school count.

Table 15 details the means for attendance, behavior days, and age at the start of high school for the five enrollment groups.

Table 15

Mean Attendance, Behavior Days, and Age at Start of High School

		Virtual			
	Traditional	> 0 ≤ .25	> .25 ≤ .5	> .5 ≤ .75	> .75 ≤ 1
Attendance percent present	93.3	89.4	90.9	91.8	93.9
Behavior days	3.9	5.7	2.3	1.2	0.1
Age in years at high school start	14.5	14.5	14.5	14.5	14.6

The highest attendance rate was for students with the most time in a virtual school, even slightly exceeding attendance for traditional students. The lowest rate at 89.4% was for the virtual school attendees who spent less than 25% of their schooling in a virtual school, the same group with the lowest graduation rate. The same group also experienced the highest mean behavior days (days of in-school suspension, plus out-of-school suspension, plus days expelled) with a mean of 5.7 days per student. Students who had attended the highest number of virtual school days had an average of only 0.1 behavior days. At the start of high school, the mean age showed a closeness between the five enrolment groups, with a maximum difference between means of only 0.07% of a year, or approximately 26 days range between groups.

The details for students who were on track at the end of 9th grade are in Table 16. To be "on track," students must have completed six units by the end of their 9th grade school year.

Table 16

9th Grade on Track

	Traditional	Virtual			
		> 0 ≤ .25	> .25 ≤ .5	> .5 ≤ .75	> .75 ≤ 1
Yes	92,055	5,233	1,052	295	302
No	25,980	4,657	854	235	238
Percent on track	78.0	52.9	55.2	55.7	55.9

The spread between students who had attended virtual schools was substantial for all groups compared to students in a traditional school with a 22.1% higher number for traditional students (78.0%) over the most successful virtual group (55.9%) and a 25.1% spread between the lowest-performing virtual group (52.9%) and the traditional group.

Tables 17 and 18 detail the percent of graduates broken down by ethnicity. Previously seen patterns continue with Asian and White students having the highest success rates, with American Indian and Alaska Natives struggling the most. Another pattern that persisted in these tables was that traditional students had the highest graduation rates and that virtual graduation rates were higher when they had more time in virtual school settings than those with less time.

Table 17

Percent of Four-Year Graduates by Enrollment Group and Ethnicity

		Virtual			
Ethnicity	Traditional	$> 0 \leq .25$	$> .25 \leq .5$	$> .5 \leq .75$	$> .75 \leq 1$
Asian	93.2	63.7	81.1		
Black or African American	73.1	46.1	61.1		
Other	82.9				
Hispanic or Latino	78.4	45.7	71.1	58.9	71.1
American Indian or Alaska Native	68.8	42.8	50.0		
Multi-Ethnic	83.0	50.1	54.8	72.4	70.0
Hawaiian or Pacific Islander	79.7	56.5			
White	84.7	52.5	64.2	72.4	75.7

Note. Groups with $n < 20$ were omitted.

The patterns of groups struggling the most are consistent in Tables 17 and 18, though several data points were omitted because of small *n*.

Table 18

Percent of Five-Year Graduates by Enrollment Group and Ethnicity

		Virtual			
Ethnicity	Traditional	$> 0 \leq .25$	$> .25 \leq .5$	$> .5 \leq .75$	$> .75 \leq 1$
Asian	94.4	69.2	95.2		
Black or African American	76.6	50.9			
Other	81.5				
Hispanic or Latino	80.9	49.6	77.0	73.0	80.0
American Indian or Alaska Native	70.3	49.3			
Multi-Ethnic	84.7	54.1	65.1	73.7	73.3
Hawaiian or Pacific Islander	80.4				
White	86.1	55.2	67.5	75.2	81.1

Note. Groups with $n < 20$ were omitted.

Black/African American, Hispanic, and American Indian/Alaska Native groups had success rates under or near 50% in both analyses for the virtual group with less than 25% virtual enrolment.

When Gender was analyzed by enrollment group in Table 19, previously seen patterns remained.

Table 19

Percent of Graduates by Enrollment Group and Gender

			Virtual				
		Traditional	> 0 ≤ .25	> .25 ≤ .5	> .5 ≤ .75	> .75 ≤ 1	All Groups
Four-Year							
	Female	86.5	55.6	68.3	70.3	75.8	83.5
	Male	79.7	46.0	60.8	70.1	74.1	77.2
Five-Year							
	Female	87.9	57.8	72.0	75.3	80.1	85.1
	Male	81.8	50.1	65.4	72.1	80.4	79.5

Females in Table 19 showed a higher level of success in all but one of the categories compared to their male peers. Male and female students' graduation performance was closest for the enrollment group that attended virtual school for more than 75% of their school days. Additionally, the enrollment groups' performance patterns held, with a particular concern for males in the virtual group with less than 25% enrollment; in this category, only 46.0% of males became graduates in the four-year analysis.

Research Question 2

Research Question 2: Do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates?

The analysis method used to explore the second research question was logistic regression, which attempts to connect available indicators to a binary outcome. This analysis began with examining individual indicators to assess their contribution to the model and assessed intercorrelations and collinearity to arrive at a final multivariate model (Field, 2013; Muijs, 2011).

Univariate analysis of indicators. The complete dataset included many factors that could be analyzed to determine their influences on graduation. The procedure for assessing if an indicator was predictive of an outcome and will offer a useful contribution in a logistic regression model is to complete a univariate regression, which means to test each indicator on its own for its predictive ability. Once these tests were complete, indicators that have $p > .05$ were eliminated. However, in large datasets, such as this one, most indicators will test out at $p < .001$. Therefore, pseudo R squared values were examined to determine which variables would most strongly contribute to the predictive model. The indicators that were considered but not included are shown in Table 20; these include gender, ethnicity, and several education programs.

Ethnicity indicators were looked at in two ways. Ethnicities were dummy coded into separate variables and were also tested as a single categorical variable. Several of these individual ethnicity indicators had p values that were not significant. In all cases, the Cox and Snell R^2 and Nagelkerke R^2 values showed that ethnicity would contribute only a small amount to the model, even when the p values were significant. Male and female genders had very different graduation outcomes, with females graduating at much greater numbers than males. However, the Cox and Snell

R^2 and Nagelkerke R^2 also showed that gender contributed very little to predicting graduation outcome.

Participation in several educational programs was examined to see if there was a relationship with graduation. Participants in many of these programs had graduation rates that were very different from the percentage of Oregon students as a whole. However, participation in these programs and the demographic factors listed in Table 20 were found to have a weak predictive relationship to graduation outcome based on the pseudo *R* squared results. These indicators were therefore not used in the analysis.

Table 20

Univariate Analysis of Indicators for Five-Year Graduation Outcomes That Were Not Included in the Model

	Likelihood Ratio			95% CI for Odds Ratio				
Indicator	χ2	*p*	Beta	Lower	Odds Ratio	Upper	Cox & Snell R^2	Nagelkerke R^2
Female	474.049	*	0.388	1.1424	1.475	1.527	.005	.009
Male	460.706	*	-0.383	0.658	0.682	0.706	.005	.009
American Indian or Alaska Native	178.261	*	-0.799	0.403	0.450	0.503	.002	.003
Asian	426.359	*	1.220	2.950	3.386	3.886	.005	.008
Black or African American	70.207	*	-0.440	0.583	0.644	0.711	.001	.001
Hawaiian or Pacific Islander	3.519	.056	-0.198	0.670	0.821	1.005	*	*
Hispanic or Latino	114.959	*	-0.227	0.765	0.797	0.830	.001	.002
Multi-ethnic	0.314	.575	-0.022	0.908	0.979	1.055	*	*
Ethnicity other	0.026	.873	0.079	0.414	1.082	2.826	*	*
White	78.852	*	0.164	1.137	1.178	1.221	.001	.002
Ethnicity categorical variable	778.423						.009	.015
Economically disadvantaged	214.853	*	-0.265	0.741	0.767	0.795	.002	.004
504	7.022	.006	-0.346	0.552	0.708	0.907	*	*
Indian education	62.686	*	-0.548	0.508	0.578	0.658	.001	.001
Individual Education Plan	27.444	*	-0.130	0.836	0.878	0.921	*	.001
English language learner	36.497	*	-0.142	0.829	0.868	0.908	*	.001
Migrant education	2.296	.126	-0.090	0.814	0.914	1.026	*	*

Note: * < .001.

The indicators that were chosen for the final model are shown in Table 21. As shown in previous research, the most reliable indicators of graduation were attendance, behavior, and course performance, often called the ABCs of graduation (Mac Iver & Messel, 2013). The univariate analysis of factors strongly supported this research, with 9th grade on track (completing six credits during 9th grade) being the most substantial single factor based on Nagelkerke R^2 (.294), which makes it highly predictive even if it were the only indicator examined. Attendance was the next strongest indicator based on Nagelkerke R^2 (.291). Both attendance and being on track have a positive relationship to graduation, as indicated by the odds ratio, which in both cases was above one. Behavior incidents, which have an odds ratio of less than one, showed that having more behavior incidents decreased the chances of a student graduating. While behavior does contribute to the model, it is much lower than attendance and ninth-grade on track, with its Nagelkerke $R^2 = .064$. The strongest predictor outside of the ABCs was mobility with Nagelkerke $R^2 = .179$. Larger numbers of schools attended demonstrated an increased risk of not graduating (odds ratio = 0.721). Also contributing to the model with lesser values were the student's age at the start of high school (overage), being identified as a special education student, or being identified as talented and gifted.

The indicator with the lowest contribution to that final model was the ratio of school days attended in a virtual setting. This indicator had the lowest impact on the model; however, it was included since it is the study's focus. Attending a virtual school had a small negative impact on a student's likelihood of graduating (odds ratio

= 0.984). Its predictive ability, as shown in its pseudo R squared values, was low compared to the other indicators with Nagelkerke R^2 = .007.

Table 21

Univariate Analysis of Indicators for Five-Year Graduation Outcomes That Were Included in Model

	Likelihood Ratio		95% CI for Odds Ratio				
Indicator	$\chi 2$	Beta	Lower	Odds Ratio	Upper	Cox & Snell R^2	Nagelkerke R^2
Attendance percent present	17,072.000	0.232	1.256	1.261	1.267	.177	.291
Behavior percent days present	3,490.809	-0.500	0.592	0.606	0.621	.039	.064
9th grade on track	17,184.867	2.498	11.684	12.157	12.649	.179	.294
Age at start of high school	196.652	-0.708	0.472	0.493	0.514	.012	.019
Retained during K-8	1,112.870	-1.162	0.293	0.313	0.334	.013	.021
Special education	1,804.943	-1.000	0.352	0.368	0.385	.020	.034
Talented and gifted	1,002.806	1.626	4.470	5.082	5.782	.011	.019
Virtual school days out of total enrollment	362.320	-0.017	0.982	0.984	0.985	.004	.007
Mobility (count of schools attended)	10,078.721	-0.334	0.711	0.716	0.721	.109	.179

Note: $p < .001$.

Testing inter-correlations of a predictive model shows if variables measure the same thing or measure something different. Higher levels of correlation approaching one indicate that a condition of multicollinearity is present and that two variables measure the same or a similar thing. As Table 22 showed, there are no concerns of inter-correlations in the chosen variables. The strongest relationships shown are between attendance and 9th grade on-track, which is shown as a negative relationship, and age at the start of high school and retention which is also a negative relationship. The variables in Table 22 measure different things, which suggests that their inclusion in the model is worthwhile.

Table 22

Inter-Correlations of Predictor Variables

		1	2	3	4	5	6	7	8	9
1	Attendance	1.00								
2	Behavior	0.08	1.00							
3	9th grade on track	-0.36	0.11	1.00						
4	Age at start of high school	0.06	-0.01	0.01	1.00					
5	Special education	0.03	-0.01	0.08	-0.06	1.00				
6	Talented and gifted	-0.07	0.01	-0.07	0.01	0.06	1.00			
7	Virtual school days out of total enrollment	0.03	0.03	0.08	0.00	0.03	0.03	1.00		
8	Mobility (count of schools attended)	0.18	-0.13	0.12	0.05	-0.09	0.02	0.01	1.00	
9	Retained during K-8	0.00	0.01	0.01	-0.28	0.11	0.01	-0.02	-0.14	1.00

Multi-collinearity results are shown in Table 23. The VIF measurement must be higher than four to be of concern, and tolerance numbers must be less than 0.02.

Table 23

Collinearity Statistics

Predictor	VIF	Tolerance
Attendance	1.30	0.769
Behavior	1.07	0.937
9th Grade on track	1.30	0.772
Age at start of high school	1.11	0.903
Special education	1.07	0.935
Talented and gifted	1.03	0.973
Virtual school days out of total enrollment	1.01	0.987
Mobility (count of schools attended)	1.17	0.853
Retained during K-8	1.14	0.875

VIF and tolerance measurements, which are all near one, show little multi-collinearity between the selected variables. VIF numbers near 1 are not collinear.

Multivariate model. The final multivariate model developed to address the second research question is shown in Table 24. All variables had significant *p* values (< .001). The most informative column in this table is the Wald statistic, which shows the relative impact of an indicator on the final model, with a higher number indicating a greater impact. For Oregon students, 9^{th} grade on track is the most contributing indicator, followed by attendance, and mobility, with other indicators contributing to the model at lower rates.

Table 24

Multivariate Model

Predictor	Estimate	SE	Wald Z^2	p-value
Attendance	0.162	0.002	7,419.36	< .001
Behavior	-0.157	0.008	388.38	< .001
9th Grade on track	1.773	0.019	9,162.49	< .001
Age at start of high school	-0.411	0.023	307.09	< .001
Special education	-0.537	0.024	516.03	< .001
Talented and gifted	0.532	0.058	83.30	< .001
Virtual school days out of total enrollment	-0.012	0.001	194.30	< .001
Mobility (count of schools attended)	-0.206	0.003	3,495.07	< .001
Retained during K-8	-0.213	0.039	30.58	< .001

Note: Log Likelihood = 81,772.034.

Tables 25 and 26 show the four-year results from the same model but separated in two different ways. Table 25 shows the models by school type, while Table 26 shows the model by enrollment group. The most notable change in how the groups were separated was the impact on the indicators' significance. The smaller groups had variables that lost significance. This was particularly important when looking at how the model predicted the outcome for the students who spent the most time enrolled in a virtual school. Participant totals in the virtual school enrollment groups were much smaller than traditional students, whose results always remained significant for all indicators.

In both Tables 25 and 26, the Cox and Snell R^2 and Nagelkerke R^2 showed high levels for all analyses from these models, where a result of one would have been a perfect fit. This suggests that this model offers a high level of predictive ability for virtual and traditional students. However, it is higher for traditional students where it correctly predicted 88.1% of traditional student graduation outcomes. When attempting to predict the outcomes for any student who had ever attended a virtual school, the prediction dropped to 75.3%. For students who had attended more than half of their schooling in a virtual environment, the predictive accuracy moved up to 78.8%. In all cases, the sensitivity and specificity show that the model was more predictive of graduates than those who would not graduate.

Table 25

Logistic Regression of Four-Year Graduation Rates by School Type

Indicator	All Students	Traditional	Any Virtual	>.5 Virtual
Attendance	1.18 (1.17–1.18)*	1.18 (1.17–1.18)*	1.14 (1.13–1.15)*	1.16 (1.14–1.18)*
Behavior	0.86 (0.84–0.87)*	0.85 (0.84–0.86)*	0.86 (0.82–0.90)*	0.66 (0.51–0.85)*
9th grade on track	5.89 (5.68–6.11)*	6.21 (5.97–6.47)*	4.38 (4.02–4.77)*	4.98 (4.10–6.06)*
Age at start of high school	0.66 (0.63–0.69)*	0.65 (0.62–0.69)*	0.69 (0.62–0.77)*	0.76 (0.62–0.92)*
Special education	0.59 (0.56–0.61)*	0.55 (0.52–0.58)*	0.75 (0.66–0.85)*	0.52 (0.39–0.71)*
Talented and gifted	1.70 (1.52–1.91)*	1.68 (1.48–1.91)*	1.63 (1.22–2.19)*	1.36 (0.56–3.34)
Virtual school days out of total enrollment	0.99 (0.99–0.99)*	†	1.01 (1.00–1.01)*	1.00 (0.99–1.00)*
Mobility (count of schools attended)	0.81 (0.81–0.82)*	0.82 (0.81–0.82)*	0.90 (0.88–0.91)*	0.87 (0.83–0.91)*
Retained during K-8	0.81 (0.75–0.87)*	0.76 (0.70–0.82)*	1.03 (0.87–1.23)	1.21 (0.83–1.75)
Sensitivity	0.951	0.960	0.802	0.890
Specificity	0.532	0.496	0.694	0.575
Correctly predicted	0.868	0.881	0.753	0.788
Model χ^2	48,414	39,825	4,534	1,093
Cox & Snell R^2	.309	.286	.297	.307
Nagelkerke R^2	.491	.478	.397	.429
Hosmer and Lemeshow R^2	<.001	<.001	<.001	<.001
n	130,901	118,035	12,866	2,976

Note: Data in odds ratio (95% confidence interval).

*Statistically significant ($p < .05$).

†This variable was excluded from the model by SPSS due to all values at zero for this enrollment group.

Notably, for its implications on Research Question 2, the odds ratios for virtual school days out of total enrollment were near 1 for all groups in Tables 25 and 26. The confidence intervals for the odds ratios were also very tight, indicating that the measure was reliable. In the analysis by enrollment groups, the virtual school enrollment indicator lost its significance. Indicators like ninth-grade on track, attendance, and mobility have much greater odds ratios, indicating their power as predictors for all students.

Table 26

Logistic Regression of Four-Year Graduation Rates by Enrollment Group

		Virtual			
Indicator	Traditional Only	> 0 ≤ .25	> .25 ≤ .5	> .5 ≤ .75	> .75 ≤ 1
Attendance	1.18 (1.17–1.18)*	1.14 (1.13–1.15)*	1.16 (1.13–1.18)*	1.17 (1.12–1.22)*	1.16 (1.11–1.21)*
Behavior	0.85 (0.84–0.86)*	0.88 (0.84–0.92)*	0.58(0.40–0.84)*	0.80 (0.52–1.22)	0.25 (0.04–1.56)
9th grade on track	6.21 (5.97–6.47)*	4.30 (3.90–4.73)*	5.90 (4.63–7.53)*	3.37 (2.12–5.35)*	4.52(2.73–7.48)*
Age at start of high school	0.65 (0.62–0.69)*	0.68 (0.60–0.77)*	0.66 (0.50–0.87)*	1.13 (0.69–1.83)	0.71 (0.48–1.04)
Special education	0.55 (0.52–0.58)*	0.81 (0.70–0.93)*	0.52 (0.36–0.74)*	0.54 (0.26–1.10)	0.55 (0.22–1.36)
Talented and gifted	1.68 (1.48–1.91)*	1.72 (1.27–2.34)*	2.53 (0.71–8.96)	0.24 (0.05–1.25)	0.83 (0.07–9.62)
Virtual school days out of total enrollment	†	1.02 (1.03–1.03)*	0.99 (0.98–1.01)	0.98 (0.95–1.01)	0.99 (0.96–1.02)
Mobility (count of schools attended)	0.82 (0.81–0.82)*	0.90 (0.89–0.92)*	0.89 (0.85–0.94)*	0.83 (0.75–0.93)*	0.80 (0.67–0.95)*
Retained during K-8	0.76 (0.70–0.82)*	1.00 (0.82–1.22)	1.39 (0.86–2.24)	1.60 (0.64–4.03)	0.67 (0.28–1.58)
Sensitivity	0.960	0.767	0.879	0.925	0.938
Specificity	0.496	0.716	0.651	0.513	0.444
Correctly predicted	0.881	0.742	0.791	0.802	0.815
Model χ^2	39,825	3,251	776	155	166
Cox & Snell R^2	.286	.280	.334	.254	.266
Nagelkerke R^2	.478	.374	.460	.361	.394
Hosmer & Lemeshow R^2	<.001	<.001	.108	.749	.315
n	118,035	9,890	1,906	530	540

Note: Data in odds ratio (95% confidence interval).

*Statistically significant ($p < .05$).

†This variable was excluded from the model by SPSS due to all values at zero for this enrollment group.

The one indicator that was the most different when comparing virtual and traditional students was behavior. For the two groups of students in Table 26 that attended the most virtual school, the behavior indicator lost its significance. Special education and age at the start of high school also lost their significance in the two groups of students who attended the most virtual school. These two predictors have a much lower impact on the model when looking at their Wald statistics from Table 24 and their Cox and Snell R^2 and Nagelkerke R^2 from Table 21. Talented and gifted also lost their significance for the enrollment groups with more than 25% virtual school attendance. But it was also a weak predictor based on its Wald statistic from Table 24 and Cox and Snell R^2 and Nagelkerke R^2 from Table 21.

The same analysis from Tables 25 and 26 was repeated with five-year graduation data with the results presented in Tables 27 and 28. Similar patterns were seen in both analyses, while some indicators lost significance due to the smaller sample size. In the school type analysis in Table 27, behavior, age at the start of high school, talented and gifted, and virtual school attendance lost statistical significance for students with more than half their attendance in a virtual school environment. Additionally, special education lost its statistical significance when looking at students who had attended any amount of virtual school.

Table 27

Logistic Regression of Five-Year Graduation Rates by School Type

Indicator	All Students	Traditional	Any Virtual	>.5 Virtual
Attendance	1.16 (1.16–1.17)*	1.16 (1.16–1.17)*	1.14 (1.12–1.15)*	1.11 (1.07–1.14)*
Behavior	0.88 (0.87–0.89)*	0.87 (0.86–0.89)*	0.90 (0.86–0.94)*	0.88 (0.53–1.47)
9th grade on track	5.21 (4.95–5.46)*	5.52 (5.24–5.80)*	3.76 (3.38–4.18)*	3.27 (2.10–5.09)*
Age at start of high school	0.61 (0.58–0.65)*	0.64 (0.56–0.64)*	0.65 (0.56–0.74)*	0.72 (0.49–1.06)
Special education	0.67 (0.63–0.71)*	0.63 (0.59–0.67)*	0.87 (0.74–1.01)*	0.44 (0.22–0.89)*
Talented and gifted	1.59 (1.38–1.83)*	1.61 (1.38–1.89)*	1.32 (0.93–1.88)	0.78 (0.09–6.65)
Virtual school days out of total enrollment	0.99 (0.99–0.99)*	†	1.01 (1.00–1.01)*	1.00 (0.98–1.01)
Mobility (count of schools attended)	0.82 (0.81–0.83)*	0.82 (0.82–0.83)*	0.90 (0.88–0.92)*	0.84 (0.75–0.93)*
Retained during K-8	0.78 (0.71–0.86)*	0.73 (0.66–0.81)*	1.00 (0.81–1.24)	3.19 (1.19–8.54)*
Sensitivity	0.955	0.964	0.814	0.942
Specificity	0.482	0.446	0.655	0.300
Correctly predicted	0.870	0.885	0.748	0.794
Model χ^2	28,898	23,732	2,725	143
Cox & Snell R^2	.282	.260	.278	.186
Nagelkerke R^2	.463	.452	.374	.282
Hosmer and Lemeshow R^2	<.001	<.001	<.001	.361
n	87,291	78,916	8,375	695

Note: Data in odds ratio (95% confidence interval).

*Statistically significant ($p < .05$).

†This variable was excluded from the model by SPSS due to all values at zero for this enrollment group.

Students who had been retained in K-8 but attended more than half of their education virtually had a much better chance of graduating in their fifth year than an analysis of four-year graduation rates. While the four-year analysis in Table 25 saw an odds ratio of 1.21 for students who had been retained, the result was not significant. In comparison, the five-year analysis from Table 27 saw the same grouping with an odds ratio of 3.19, and the result was significant. Other notable changes in the comparison of Tables 25 and 27: behavior, age at the start of high school, and virtual school attendance lost their statistical significance for students who spent more than half of their time attending virtual schools. The Cox and Snell R^2 and Nagelkerke R^2 values were also lower for virtual school attendees in the five-year analysis by school type. The model's ability to accurately predict graduation was most precise for students in traditional school at 88.5%, and least precise for the students in the any virtual category with a 74.8% correct rate of prediction. Sensitivity was highest when all Oregon students were considered together, and specificity was strongest for virtual students when looked at together. The specificity for students in a virtual environment for more than half of their schooling was noticeably lower at .300, indicating difficulty for the model in predicting which students in this group would not be successful. This may be a result of the many indicators that lost statistical significance with this group.

In Table 28, the model's results showed that reduced participants in the analysis caused difficulty in maintaining the model as group sizes decreased. For the enrollment group with the highest virtual enrolment, only three variables remained statistically significant; these were attendance, 9^{th} grade on track, and mobility.

However, even for this enrollment group, the accuracy of prediction remained at 84%. The most successful prediction remained with the traditional student group at 88.5%. The pattern of which kind of prediction was most successful also continued in this analysis with much higher sensitivity ratios than specificity ratios.

Table 28

Logistic Regression of Five-Year Graduation Rates by Enrollment Group

		Virtual			
Indicator	Traditional Only	> 0 ≤ .25	> .25 ≤ .5	> .5 ≤ .75	> .75 ≤ 1
Attendance	1.16 (1.16–1.17)*	1.13 (1.12–1.15)*	1.18 (1.14–1.21)*	1.11 (1.06–1.16)*	1.11 (1.07–1.16)*
Behavior	0.87 (0.86–0.89)*	0.90 (0.86–0.95)*	0.89 (0.75–1.05)	0.96 (0.52–1.64)	0.10 (0.01–1.47)
9th grade on track	5.52 (5.24–5.80)*	3.65 (3.24–4.11)*	5.29 (3.84–7.28)*	3.15 (1.77–5.63)*	3.73 (1.85–7.54)*
Age at start of high school	0.64 (0.56–0.64)*	0.68 (0.58–0.80)*	0.52 (0.36–0.74)*	0.87 (0.48–1.57)	0.60 (0.35–1.03)
Special education	0.63 (0.59–0.67)*	0.98 (0.82–0.16)	0.53 (0.35–0.81)*	0.47 (0.19–1.13)	0.33 (0.11–1.03)
Talented and gifted	1.61 (1.38–1.89)*	1.26 (0.87–1.83)	5.29 (0.65–43.24)	0.39 (0.04–4.00)	‡
Virtual school days out of total enrollment	†	1.03 (1.02–1.04)*	0.99 (0.97–1.02)	0.99 (0.96–1.03)	0.99 (0.95–1.03)
Mobility (count of schools attended)	0.82 (0.82–0.83)*	0.91 (0.89–0.93)*	0.85 (0.80–0.91)*	0.89 (0.79–1.01)	0.67 (0.53–0.55)*
Retained during K-8	0.73 (0.66–0.81)*	0.86 (0.68–1.10)	1.43 (0.76–2.68)	2.38 (0.72–7.91)	5.79 (0.98–34.09)
Sensitivity	0.964	0.777	0.879	0.927	0.964
Specificity	0.446	0.682	0.651	0.337	0.338
Correctly predicted	0.885	0.734	0.791	0.772	0.840
Model χ^2	23,732	1,956	496	65	84
Cox & Snell R^2	.260	.262	.330	.170	.217
Nagelkerke R^2	.452	.350	.464	.248	.345
Hosmer & Lemeshow R^2	<.001	.011	.897	.831	.664
n	78,916	9,890	1,264	351	344

Note: Data in odds ratio (95% confidence interval).

*Statistically significant ($p < .05$).

†Variable excluded from model by SPSS due to all values at zero for this enrollment group.

‡SPSS computed an exceptionally high number (113,791,560.61) and reported no results for the confidence interval. It was rerun without this variable and other results had small changes; this result was not reported but other data was kept for consistency.

Research Question 3

Research Question 3: What combination of indicators is most useful for predicting a virtual student's graduation outcome?

A forward stepwise logistic regression analysis was used to determine the most useful combination of indicators to predict graduation outcomes for virtual students. This multi-step method runs the model with the indicators ordered by most to least predictive, then continues adding indicators at progressive steps until no improvement can be made in the model. If an indicator did not add to the predictive ability of the model, it was not included. For this analysis, students were selected who had attended a virtual school in Oregon for at least 75% of their education. This was the smallest of the enrollment groups. As a result, some of the significant indicators for the second research question's analysis lost their significance in this method and were excluded from the analysis by SPSS.

The indicators that were included in each step are detailed in Table 29. An important distinction between this analysis and the literature on graduation rates was that behavior as a predictor was of limited usefulness for this group of students. SPSS did not choose it for use in the four-year analysis, though it was included in the fifth step of the five-year analysis.

Table 29

Indicators Chosen for Model in Forward Stepwise Analysis of Virtual High School Graduation Outcome

Step	Four-year	Five-year
1		
	Attendance	Attendance
2		
	Attendance	Attendance
	9th grade on track	9th grade on track
3		
	Attendance	Attendance
	9th grade on track	9th grade on track
	Mobility	Mobility
4		
	Attendance	Attendance
	9th grade on track	9th grade on track
	Age at start of high school	Age at start of high school
	Mobility	Mobility
5		
		Attendance
		Behavior
		9th grade on track
		Age at start of high school
		Mobility
Not Included in Model		
	Behavior	Retained K-8
	Retained K-8	Special Education
	Special Education	Talented and Gifted
	Talented and Gifted	Virtual Attendance
	Virtual Attendance	

Note. The four-year analysis concluded in step 4.

Both analyses excluded retention during K-8, identified as special education, and identified as talented and gifted. The virtual attendance indicator was also excluded, likely because all students had high values on this ratio.

The goodness of fit statistics for the two analyses are shown in Tables 30 and 31.

Table 30

Four-Year Graduation Outcome Model Fit for Virtual Students by Step

	Step 1	Step 2	Step 3	Step 4
Sensitivity	0.946	0.933	0.948	0.941
Specificity	0.281	0.370	0.415	0.393
Predicted Correctly	0.780	0.793	0.815	0.804
Cox & Snell R^2	.188	.239	.252	.258
Nagelkerke R^2	.279	.354	.373	.382
Hosmer and Lemeshow R^2	.042	.057	.380	.325
Model $\chi 2$	112.625	147.311	156.511	161.091
Log likelihood	494.697	460.011	450.811	446.231

In interpreting these tables, increasing values in all categories except log-likelihood demonstrate an improvement. For log-likelihood, a decrease in value shows an improved model. In Table 30, the model was improved at each step. However, a contradictory result is seen in the sensitivity, specificity, and percentage correct. The fourth step is less accurate in predicting the final graduation outcome when compared to the third. This may bring into question the usefulness of age at the start of high school for virtual students as an indicator.

The five-year model fit in Table 31 shows consistent improvements in all model fit measurements.

Table 31

Five-Year Graduation Outcome Model Fit for Virtual Students by Step

	Step 1	Step 2	Step 3	Step 4	Step 5
Sensitivity	0.971	0.964	0.960	0.960	0.964
Specificity	0.206	0.221	0.265	0.279	0.309
Predicted Correctly	0.820	0.817	0.823	0.826	0.834
Cox & Snell R^2	.128	.158	.179	.188	.198
Nagelkerke R^2	.204	.251	.284	.299	.314
Hosmer and Lemeshow R^2	.052	.141	.291	.680	.710
Model $\chi2$	112.625	147.311	156.511	161.091	161.091
Log likelihood	494.697	460.011	450.811	446.231	446.231

As in the analysis in Table 30, there is unexpected movement in the sensitivity and specificity. Sensitivity is highest in step one, while specificity is highest in step five. The predicted correct figure in step five shows the best combination of sensitivity and specificity and overall predictive ability.

Table 32 shows the odds ratios and confidence intervals for the indicators in the two analyses.

Table 32

Logistic Regression of Four-Year and Five-Year Graduation Rates for Virtual Students Using Forward Stepwise Method

Indicator	Four-Year	Five-Year
Attendance	1.16 (1.11–1.20)*	1.11 (1.06–1.16)*
Behavior	†	0.09 (0.01–1.40)
9th grade on track	4.60 (2.80–7.57)*	3.72 (1.87–7.39)*
Age at start of high school	0.67 (0.46–0.97)*	0.59 (0.35–0.99)
Mobility (count of schools attended)	0.79 (0.68–0.92)*	0.79 (0.59–0.89)*
n	540	344

Note: Data in odds ratio (95% confidence interval).

*Statistically significant ($p < 0.05$).

†This variable was excluded from the model by SPSS.

More attendance and being on track in 9th grade were positive predictors for both analyses. Age at the start of high school and mobility were both negative indicators. Behavior was only included in the five-year model. The five-year analysis also had age at the start of high school in the model, even though the analysis marked this variable as not statistically significant.

In logistic regression, the Wald statistic explains the relative impact of variables on the model's outcome. Table 33 shows the results of this analysis. The Wald statistic is not used to compare models. Instead, it is used to compare the variables within the same model, using the same data. Larger samples will create models with higher Wald statistics. For the comparison in Table 33, the much higher numbers in the four-year analysis were associated with the larger sample size.

However, in looking at each analysis on its own, the indicators' impact can be seen, and their relative importance can be compared.

Table 33

Wald Statistic Comparison of Virtual School Graduation Models

	Wald Z^2	
Indicator	Four-Year	Five-Year
Attendance	51.243	23.451
Behavior	†	2.958
9th grade on track	36.176	14.089
Age at start of high school	4.569	3.979
Mobility (count of schools attended)	9.270	9.611
n	540	344

†This variable was excluded from the model by SPSS.

In both analyses, attendance was the strongest indicator, followed by 9th grade on track, mobility, and age at the start of high school. Behavior was a contributor to the five-year outcome model, but it contributed the least of any variable. In the analysis from Table 24, which showed the Wald statistics for all students, including traditional, the ninth-grade on-track indicator was a stronger contributor to the model than attendance.

Summary of the Results Chapter

This chapter reviewed descriptive statistics for three high school cohorts and whether they successfully completed high school. The student’s graduation outcome was disaggregated by demographic group and program participation. Then graduation outcome was compared by enrolment groups (i.e., traditional and varying amounts of virtual school attended). Next, logistic regression was performed utilizing the indicators that were available in the Oregon Department of Education database. Finally, the indicators were analyzed using a forward stepwise logistic regression in the context of virtual school to examine which indicators might be most effective for predicting an outcome in this setting. Throughout the results chapter, notable impacts and differences were pointed out for each analysis. In the following chapter, the implications and limitations of these results will be discussed in the context of the relevant literature, and suggested areas of future research will be highlighted.

Chapter 5: Discussion

The purpose of this causal-comparative study was to compare graduation outcomes, defined as completing high school within five years, for students who learned online in Oregon virtual schools to students who attended traditional schools. The study used data from the Oregon Department of Education to examine the connection between predictive indicators and graduation outcomes. Data were analyzed using descriptive statistics and logistic regression. The study investigated graduation outcomes in the context of virtual school attendance to see if a virtual setting had different outcomes compared to traditional school settings. The following three research questions guided the focus of analysis:

1. When examining the ratio of the number of school days spent in a virtual school setting to the student graduation rates, does the increase of days in a virtual setting impact the likelihood of high school graduation, defined as completing 24 credits?

2. Do predictive graduation indicators from the literature (i.e., attendance, behavior, demographics, performance, and mobility) explain the discrepancy, if any, in virtual and non-virtual Oregon five-year high school graduation rates?

3. What combination of indicators is most useful for predicting a virtual student's graduation outcome?

Chapter 1 introduced virtual schooling in the context of graduation results. Preliminary research showed that virtual schools graduate fewer students compared to their traditional school peer institutions. The chapter continued with a statement of the problem, identified the research gap, purpose statement, and research questions. These set the study's focus on furthering the understanding of graduation in virtual schools and increasing the knowledge of whether virtual schooling leads to poor graduation outcomes or if other factors better explain any identified performance gap.

Chapter 2 was a review of the literature on graduation outcomes. It addressed the historical context of high school graduation, its rate of growth, and its stagnation. It then examined long-term life outcomes for students who failed to graduate and looked at graduation in the context of virtual schools in the historical context of Oregon's struggle to match improvements in other states. Next, the literature on graduation early warning indicators was surveyed, which pointed out which previously studied indicators were most successful. Finally, it addressed the gap in research on graduation in virtual schools and connected it to a conceptual framework and valuable indicators for this study.

A search of the literature found that there was limited research available on graduation in virtual schools. Where it did exist, there was little explanation for why results might be different between traditional and virtual schools. The research literature examined in Chapter 2 narrowed the indicators to be reviewed, showed a path to combining indicators to improve their likelihood of a successful prediction, and demonstrated that if only one indicator could be chosen, it was most likely to be ninth-grade on-track.

In Chapter 3, the methodology for the study was explained in detail. The indicators that were described, the source of data and participants were detailed, and the statistical tools and analysis were presented. Logistic regression as an analysis tool was explained in how it works, in what the generated statistics mean, and how they are evaluated. In Chapter 4, Research Question 1 was addressed through descriptive statistics, and logistic regression models were used to address Research Questions 2 and 3.

Discussion of Results

Results for Research Question 1: The data analyzed for the first research question showed a large gap in performance between students in virtual settings compared to students in traditional settings. In a simple comparison between virtual and traditional students, those in virtual school settings had lower graduation rates. However, when data were separated by enrollment group, a more nuanced picture emerged. Only a small number of Oregon students spent more than 75% of their enrollment in a virtual setting. These students' graduation rates were approaching those of traditional students. The students of greatest concern who had the lowest graduation rates spent some time in both systems but most of their time in the traditional system. This pattern held for different genders and ethnic groups.

Results for Research Question 2: The second research question results showed that the understanding of what indicators predict graduation from the literature in traditional student populations worked well in predicting the outcomes for Oregon high school students. They were also predictive for virtual school students but less strongly when compared to traditional students. The most successful predictors for virtual students were attendance, 9^{th} grade on track, and mobility. Depending on how students were grouped, behavior, which was a successful predictor in the literature, was less powerful for virtual students. For students who attended more school in a virtual setting, behavior as a predictor lost statistical significance. Therefore, its usefulness in predicting a virtual school graduation outcome was put into question in the context of this study.

The literature-based graduation indicators worked well for predicting if a virtual student would become a graduate. They did not work as well predicting if the student would become a non-graduate. Further, attending a virtual school itself was not a strong predictor of graduating or of not graduating. The odds ratios in all analyses for attendance in a virtual school were near 1. Though it was sometimes below one, which suggests a negative influence on the graduation outcome, it appears from the model that this had little impact on the student's outcome. On its own, as an indicator, attending a virtual school had the lowest Nagelkerke $R^2 = .007$ (Table 21) of the nine indicators, which suggests that its contribution to the model was about 0.07%. Of the nine indicators used for Research Question 2, attending a virtual school had the third-lowest Wald statistic (194.30), as shown in Table 24, further indicating that its predictive abilities were limited.

Results for Research Question 3: The final research question results gave additional evidence that some indicators that have been found useful for predicting graduation outcomes for high school students may need reevaluation when used as predictive indicators for virtual high school students. Attendance and ninth grade on track remained strong. However, behavior was not a strong predictor in the virtual group that was analyzed, in contrast to findings in traditional settings. Mobility and age at the start of high school added more to the model than behavior, which was unexpected compared to the graduation outcome literature. The final question's results suggest that a subset of indicators would be more successful in predicting virtual students' graduation outcomes.

Findings and Implications

Attending a virtual school is not a good predictor of whether a student will graduate. While students in virtual schools are less likely to graduate than students in traditional schools, the results of this study suggest that being a virtual student is not the cause of the lower outcome. Several pieces of evidence suggest that something else is responsible for the lower graduation rate. The following are results from the data that suggest that something else may be the cause:

1. As a predictor of graduation, attending a virtual school was the least likely indicator that was included in the model to predict a correct graduation outcome. We can see this through several statistics. The odds ratio was in all cases near 1.0, although it did sometimes show a slightly negative impact. To be predictive, the odds ratio should be either lower or higher than one.
2. For students who had attended a virtual school at any time during their education, their chances of graduating increased the more time they spent in a virtual environment. Each quartile of increased classroom time in a virtual school coincided with a dramatic increase in a positive graduation outcome (see Tables 13 and 14). Students who had spent 75% or more time in a virtual

school had nearly the same graduation outcome as students who only attended a traditional school. The results do not tell us if more time in a virtual school predicts an improvement; it seems more likely that the better performance is connected to consistency and reduced mobility.

3. The students with the lowest graduation performance were those with the highest mobility; this group was also the largest "virtual" group even though they spent less than 25% of their time in a virtual setting. This group dwarfs the students who spent most of their time in a virtual setting and therefore seems to make a disproportionate impact on virtual school graduation rates.
4. All four virtual enrollment groups had ninth-grade on-track rates that were much lower than students attending traditional schools. For the group that spent more than 75% of their time in a virtual school, their on-track rate was 55.9%, but their five-year graduation rate was 80.2%. Compared to the traditional students with an on-track rate of 78% and a five-year graduation rate of 83.0%. In this measure, it was a surprise how effective the virtual schools were at helping off-track students catch up to their peers and complete their educations.

The most likely explanation for why virtual schools have lower graduation performance is that many students choosing a virtual school have struggled in the traditional school system and might look to virtual schools as an escape, as suggested by Montgomery (2014). This explanation fits the data. Very large numbers of virtual students in this study also have been found to be highly mobile; this mobility correlates to lower graduation outcomes. Further, the least mobile virtual students were the most likely of the virtual enrolment groups to graduate. If struggling students are trying multiple schools to find a school fit that works for them, they may not be spending enough time in one model to learn how to work in its specific context. While the knowledge and standards are the same for a virtual student as they are for a traditional student, delivery is substantially different.

Students often experience difficulties when transitioning into a new school, which can be even more complicated when changing from traditional schools into virtual schools (Bueno, 2020; Fiel, Haskins, & Turley, 2013; Grim, 2019). The first semester can be challenging. Students who do not fully commit to virtual learning or only spend a brief time in the system are very likely to struggle. If they were struggling before they transitioned to a virtual school, their struggles would be intensified. Based on the data in this study, it appears that some students that move from traditional to virtual settings have not performed well and may need additional support in their transition.

Gender graduation disparities disappear in virtual environments for students who spend more time in virtual schools. The gender divide in graduation results disappeared for students who spent more than 75% of their school attendance in a virtual environment. Females graduate at higher rates than males; this phenomenon has been documented in multiple studies (Phinney, 2016; Robison et al., 2017; Stearns & Glennie, 2006). In this study, the disparity was also present when all participants were examined as a group and in some of the enrolment groups when looked at separately. However, the pattern was different for students who spent the most time in a virtual school. For these students, being more virtual seemed to erase female students' advantage in graduation attainment. This suggests virtual schooling may offer male students a place to be more successful. This may be connected to the reduction in behavior incidents that were also seen in the virtual setting. Behavior incidents are much less common in virtual settings, as seen from the data in this study.

Retained students have better graduation outcomes with more time in a virtual school. In Table 25 and 27, students who had been retained in K-8 but attended more than half of their education virtually had a much better chance of graduating in their fifth year than an analysis of four-year graduation rates. This may be advantageous for some struggling students who have chosen to attend a virtual school compared to their traditional school peers—suggesting that students who had been retained during K-8 may have a better opportunity of graduating in a virtual setting than in a traditional one.

The effectiveness of prediction models in traditional and virtual settings, as seen in this study vary. Not all indicators that were predictive in traditional schools are as useful with virtual schools. This suggests that models may need to be modified specifically to address the needs of virtual schools. The most notable indicator that loses its effectiveness is behavior, which is one of the three legs of Mac Iver and Messel's (2013) model.

Behavior is not an effective indicator in virtual schools. Behavioral events are very different and less common in a virtual setting and were found in the results to be a stronger predictor in a traditional setting compared to a virtual setting where they were less predictive of graduation. Because of the nature of virtual schools, there are fewer student-to-student interactions. Though they may sometimes meet in person, these events are much less common than student interactions in traditional settings. This change in how students interact with each other results in few behavior events in virtual school settings. This causes behavior as a predictor to lose its usefulness. With virtual students, behavior was a weak predictor and lost significance in multiple cases.

The fifth year of high school offers some students a bridge to graduation. As it has been understood in the United States, high school has been designed as a four-year program of study. However, many students do not complete their graduation requirements within those designated four years, and schools make available an additional fifth year to many students. The data analyzed in this study show that this fifth year was an essential support to many groups of students who have much better outcomes when the graduation metric includes the additional year. In Table 8, the 2013-2014 and 2014-2015 cohorts showed the difference between four-year and five-year results. The two cohorts results also demonstrated the benefit for some students of having additional time to complete their requirements as a 3.1% and 2.7% increase in positive graduation outcomes after the additional year of high school.

The fifth year of high school may be most beneficial to some groups of students that are struggling the most. Particularly, students who are male, economically disadvantaged, or African-American/Black see benefits from an additional year. When looking at the outcomes for these groups, graduation attainment was higher, and the gaps between these groups and the total population were lower in the five-year analysis (see Tables 9 and 10). Note that the population in these two analyses (four-year and five-year) had overlapping students, but they were not identical.

It is easier to predict a graduate than a non-graduate. The results in this study showed that correctly predicting sensitivity was more likely than specificity. In other words, it is easier to predict which students will be graduates than it is to predict which students will not become graduates. In every analysis in this study, the true positive ratio was always higher than the true negative ratio (see Tables 25, 26, 27, 28, 30, and 31). This points to a concern known from the literature, in attempting to assess students' risks of not graduating, there is a danger that interventions might be given to students who do not need them (Gleason & Dynarski, 2002). For example, a student identified as at-risk might be removed from more challenging classes and be placed in a credit recovery program if they were behind in credits. The risk is that it may not be certain that a student was not going to graduate, and the intervention may harm the student's chances of attending college. This example illustrates the concern that educators must take in making decisions. The outcomes are not always known.

Engagement could be the common thread or missing link. Many authors wrote about graduation indicators had a common refrain. They indicated that the major predictors of graduation: attendance, behavior, class performance, and mobility all were in some ways connected to the student's engagement with school (Balfanz et al., 2007; Ekstrom et al., 1986; Mac Iver & Messel, 2013; Rumberger & Larson, 1998).

Engagement can be challenging for schools to quantify or even to define. These measures suggest the student's lack of engagement; they are present, not involved in misbehavior, completing assignments and classes, and stay in any one school for longer. In some sense, virtual schools have an advantage over traditional schools in measuring engagement. The learning management systems and web-based curriculums offer analytics that can measure what was turned in and record how long the student spent on an assignment, what day, and what time of day. This information can inform the school's understanding of the student's engagement with the curriculum. These systems cannot measure the student's emotional connection to the school or to the school staff, which may negatively impact the student's motivation to complete high school (Legault, Green-Demers, & Pelletier, 2006).

The ABCs of graduation plus M. Mac Iver and Messel (2013) created the ABCs of graduation, which consisted of attendance, behavior, and course performance. The data in this study suggested that behavior was much less predictive of graduation outcomes for virtual students. It also indicated that mobility might be an improved addition to this model to improve its predictive power. In the case of virtual schools, mobility may be a worthwhile substitute. ABC+M might be an improved model for all students, whereas AC+M might be a better predictive model for virtual students. While the tests for multicollinearity did not find that mobility and behavior as indicators measured the same thing, there is a certain logic in the idea that mobility and behavior incidents might both be signs that a student is experiencing a greater level of chaos in their life, which could impact their school performance.

Limitations

Not all graduation indicators that have been studied could be examined from the data that was available for this study. Non-school factors such as home life, economic status, employment, pregnancy, parental education level, and other factors have been researched as possible explanations for why a student becomes a high school graduate. However, data on these indicators were not collected by the state of Oregon and are not readily available for analysis in large datasets. The collection of such data could greatly expand the understanding of student graduation outcomes.

A further limitation of this study is that data were collected and organized by numerous schools, districts, and officials of the Oregon Department of Education. The procedures that were put in place to collect these data give a reasonable level of confidence that the data were accurate. However, all collected data have errors. Because individual parts of these data have been collected by potentially thousands of different people, some of the data points were inevitably erroneous. With that caveat in mind, the total dataset's size with the records of 130,901 students provides confidence that the sample size reduced the impact of inevitable individual errors.

Delimitations

One of the central features of the methodology I chose for this study was to answer for myself: Who is a virtual student? There is no answer to such a question in the literature, and I had to decide how to organize students so that I could see how their attendance in a virtual setting impacted their graduation outcome. If another researcher were to criticize my choices, I think this choice would be an essential place to consider. In looking at the students in the dataset, a surprisingly small number of students attended a virtual school for their entire school career. Only 341 of the 130,901 students in the study attended a virtual school for their entire education. That was 0.26% of the students in the full sample. It would be challenging to make generalizable conclusions from such a small population. To deal with this problem, I chose to divide students into what were referred to as enrollment groups.

The five enrollment groups were students who had a traditional setting for all their schooling and four virtual groups that were separated by the ratio of days attended in a virtual setting. All five groups were of substantially different sizes. By dividing the groups in this way, I increased the smallest group, with the most time at a virtual school, to 541, giving the analyses better chances to find significance. This choice seemed like the best solution to creating a meaningful analysis. However, another researcher might see a need for a different choice. As virtual schooling matures, larger numbers of students who have attended much greater portions of their education using this model will make such decisions easier since there will be more data to analyze.

Future Research Needed

Future research should seek to answer the following question: Do virtual schools act as a pressure release outlet for traditional schools? Such a possibility was strongly suggested by Montgomery (2014), and the results of this study support the possibility that for a large portion of virtual students, this was what happened. The students most likely to not graduate were those that spent up to 25% of their education in a virtual setting. This same group had the highest rate of mobility. It is not a giant leap to make an argument that many in this group of struggling students had hit a proverbial eject button from the traditional schools to “escape,” as Montgomery (2014) asserted. This group also dwarfed the sizes of other virtual school attendees. There were 9,883 students who spent up to 25% of their time in a virtual setting, whereas only 540 spent 75% or more in a virtual setting. The size discrepancy alone tells us a lot about how reliable the graduation rates are at the individual school level. It hardly seems fair to give a school either the credit for a graduate or the blame for a non-graduate who spent so little of their time at a particular institution. If virtual schools are a “pressure relief outlet” for traditional schools, which the data suggest, the way we examine the results for a particular school needs to be refined and contextualized based on their student population and its unique challenges. As a result, these students’ movement into virtual schools may improve the graduation rates for traditional schools while bringing down the rates of the virtual schools.

The connection of school mobility to graduation outcome has been studied (Dalton et al., 2009; Rumberger & Larson, 1998; Silver et al., 2008), but it deserves much more attention from researchers. There are many reasons why a student becomes mobile, most of which are out of the student’s control. Nevertheless, mobility is likely a strong signal that the student will struggle. In the dataset used for this study, 8,697 students attended more than ten different schools, 300 students attended 20 or more, and one student attended 35 schools. These are the outliers, but it cannot be a surprise that students with substantially higher mobility rates will struggle, which may impact their life outcomes. These patterns are easy to see in students' records. Children with very high mobility numbers are likely experiencing very chaotic and possibly traumatic lives. Many researchers have looked at the student's connection to the school to see how it impacts learning and success (Allensworth & Easton, 2007; Hawkins et al., 2013; Rumberger & Larson, 1998; Rumberger & Lim, 2008). Not surprisingly, there is a deep relationship. A student who moved from school to school was denied deep relationships with peers and never really connected to the non-family adults in their lives is bound to struggle. The solutions to these problems are far greater than what can be tackled at the school level; this problem calls for action at the state and federal levels to find ways to help these students.

Much more study needs to be focused on virtual schools and virtual school methods of delivery. Circling back to the question: Who is a virtual student? We are brought to another question: What is a virtual school? There are ideas about how to answer this question, but there is no consensus. Is it the student's location while engaging in schooling? Is it the method of delivery? On the latter question, there are numerous variations. In the context of the COVID-19 pandemic, it seems like learning techniques that have been utilized in virtual settings are set to go mainstream and become commonplace. It is time for future researchers to emphasize how virtual learning impacts students in their graduation outcome but also in other ways: their performance in particular subjects, their levels of emotional and social well-being, and their levels of preparation for colleges and careers. Previous research has suggested that the method of learning should not impact outcomes, but there has not been enough additional research for this conclusion to become widely accepted (Cavanaugh, 2009; Cavanaugh et al., 2004). It is time for researchers to confirm this idea or to contradict it. With the dramatic increase in virtual school enrollment, too much is on the line.

The good news for researchers is that virtual schooling is new enough that there is fertile ground to learn how things are different in a virtual learning environment, what techniques work best, and what models are worthy of duplication to a broader audience that needs to know. Testing of new educational models and dissemination of their efficacy was one of the original justifications for charter schools, from which most virtual schools grew.

More data and analysis are needed to examine whether virtual schools reduce the graduation disparity for male students, as the results of this study suggest. A possible reason for this may be the decrease in negative behavior events that result in changing from traditional to virtual school models. It is possible that if this connection were confirmed, it might suggest that other groups that have had high levels of behavior incidents might also benefit from learning in a virtual environment.

Conclusion

Virtual schools are a recent development in how students attend school. They have grown both in the numbers of schools and in students who attend them. This option has offered students a more flexible way of completing their educations, allowing them to be in school at a time and place of their choosing. This gives students the opportunity to bring a flexible schedule to their day; the model may help students who have medical conditions that keep them from a traditional school, have jobs, live in rural locations, or are pursuing sports training at a high level. However, as this study has shown, our understanding of virtual schools has been incomplete due to limited research because of the new nature of this type of schooling. Many students do find these schools and the opportunities that they offer to be of great benefit. Yet, there remains work to be done, both in increased research and in further refinement of these models to improve student learning and graduation outcomes. The evolution of this model has the potential to become a powerful force in the future of education and has lessons that it may be able to teach traditional schools.

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