Online Credit Recovery in a Large School Division in Virginia: Examining Factors for Participation and On-Time Graduation

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ABSTRACT

Under the pressure of federal accountability for high schools in the United States to improve and maintain high rates of on-time graduation, online credit recovery has become an increasingly popular intervention to help students earn credit in a course that they have previously failed. While some studies have connected online credit recovery with positive outcomes for participants, others have found negative outcomes and poor learning experiences. Set in a large school division in Virginia, the purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery and (b) compare the likelihood of on-time graduation of participants with the likelihood of on-time graduation of nonparticipants. Limited to the graduation cohorts of 2019 and 2020, there were 10,010 students in the sample from the participating school division. In the sample, 27% of students were eligible to participate in online credit recovery, but only 2.3% of students participated. Binary logistic regression models were designed to identify factors associated with participation and the likelihood of on-time graduation. Covariates considered for inclusion in the model were gender, race and ethnicity, status as an English learner, status as a student with a disability, status as homeless, status as economically disadvantaged, high school grade point average, and school. Both models failed to meet goodness of fit standards and were rejected as having fit the data. No student factors were found to have explained participation, and differences in the likelihood of on-time graduation were not identified. These findings indicated that there did not appear to be systemic participation given the studied factors, reinforced by the finding that participation was

relatively uniformly distributed among the schools. The finding of a lack of significant difference in the likelihood of on-time graduation highlighted flexibility for schools in choosing their recovery interventions. State agencies may also consider collecting and publicly reporting data about student participation in online credit recovery. Opportunities for future studies include replication in other settings, particularly districts of different size and area/region, and qualitative inquiry into decisions made by school and district leaders related to credit recovery.

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GENERAL AUDIENCE ABSTRACT

Under the pressure of federal accountability for on-time graduation rates, high schools have increasingly used online credit recovery to help at-risk students. Some studies have identified positive outcomes for students in online credit recovery; however, others have found negative outcomes and poor learning experiences. Set in a large school division in Virginia, the purpose of this study was to identify factors that were associated with participation in online credit recovery and the likelihood of on-time graduation of participants compared to non-participants. Limited to the graduation cohorts of 2019 and 2020, there were 10,010 students in the sample from the participating school division, of which 2.3% of students participated. Logistic regression models were created, and covariates considered for inclusion in the model were gender, race and ethnicity, status as an English learner, status as a student with a disability, status as homeless, status as economically disadvantaged, grade point average, and school. Both models failed to fit the data well; no associated factors were found, and graduation rates were not found to be significantly different. There did not appear to have been systemic participation, and schools appear to have flexibility in offering recovery interventions. State agencies may also consider collecting and publicly reporting of data about student participation in online credit recovery. Opportunities for future studies include replication in other settings and qualitative inquiry into decisions related to credit recovery.

Dedication

To my wife, Rachel, and our children, Ellie, Abbie, and Bennett—you have sacrificed more than anyone else to support me on this doctoral journey, and I have been met with nothing less than unconditional love and support;

To my parents, John and Linda, and to my parents-in-law, Dale and Becky, for being some of my loudest and most loyal cheerleaders;

To Joe, his wife Nicole, and their son JJ, for being my closest friend and ally for over 20 years;

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And to my coworkers and colleagues who were my mentors, collaborators, and supporters that shaped me as an educator, prepared me for this journey, and saw me through it;

Thank you. This journey would not have been possible were it not for your selfless sacrifices.

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Finally, thank you to the members of my doctoral cohort. I am so glad that I had each of you to support me as someone going through the same things as I was. You were great thought partners, gave incredible feedback, provided support and encouragement when I needed it most.

Without these teams of amazing people, there is no way that I could have been successful. Thank you.

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Chapter 1

Introduction

Since 2002, the U.S. federal government has required that states develop accountability measures for improving student academic achievement and outcomes, both for all students and for traditionally-marginalized student subgroups including, but not limited to, students with disabilities (SWD), English learners (EL), Black students, and Hispanic students (Dee & Jacob, 2011; Every Student Succeeds Act [ESSA], 2015; No Child Left Behind [NCLB], 2002). One academic outcome has been the rate at which students graduate from public high school within 4 years of entering high school, informally known as the *on-time graduation rate* (OTGR; McFarland et al., 2020). Formally, the U.S. Department of Education (USDOE) has defined OTGR as the *Adjusted Cohort Graduation Rate* for state accountability purposes (McFarland et al., 2020). To increase these rates as required by NCLB, and, since 2015, ESSA, educators have increasingly turned to online learning to help students recover failed credits through an intervention called *online credit recovery* (Powell, Roberts, et al., 2015; Viano, 2021; Watson et al., 2014). Researchers and educators have identified concerns about the online recovery courses being of poor quality (Heinrich & Darling-Aduana, 2021; Powell, Roberts, et al., 2015; Viano & Henry, 2023). There has also been limited research concerning the association between student factors and participation in online credit recovery; similarly, there has been limited research regarding associations between online credit recovery and the OTGR of its participants (Rickles et al., 2018; Viano & Henry, 2023).

Using logistic regression, this quantitative *ex post facto* study created regression models designed to examine factors that may have explained participation in online credit recovery and also designed to compare odds of on-time graduation for (a) students who were never eligible for

online credit recovery, (b) students who were eligible for, but did not participate in, online credit recovery, and (c) students who participated in online credit recovery. This study used historical data from the graduating cohorts of 2019 and 2020 in a large school division in Virginia.

Historical Background

Historically, the role of the U.S. federal government in education has been secondary to the role and influence of state and local governments (Conlan, 1981). As decided by the U.S. Supreme Court, "no single tradition in public education is more deeply rooted than local control over the operation of schools" (Miliken v. Bradley, 1974, p. 742; see also San Antonio School District v. Rodriguez, 1973; Wright v. Council of City of Emporia, 1972). To manage the federal government's involvement in education, a sub-cabinet-level Department of Education was formally created by Congress in 1867 under the Department of the Interior (Conlan, 1981); this department eventually became the cabinet-level USDOE in 1980 (Kessinger, 2011). From 1860–1890, a sizeable number of politicians and educators argued against federal funding for public education, and the efforts supporting federal involvement in or funding for public K-12 schools had mostly halted from 1890–1920 (Conlan, 1981).

Following World War I, there was increased support in the United States for federal funding for vocational education and literacy efforts; however, the overall amount of funding remained negligible for schools (Conlan, 1981). Public K-12 schools in the United States received no more than one-half of one percent of their funding from the federal government from 1919-1930, rising to no more than two percent by 1940 and no more than three percent by 1950 (Conlan, 1981). By the end of World War II in 1945, movements to provide federal funding for public schools increased in popularity due to changes in social and political priorities and pressures (Conlan, 1981).

Fight for Civil Rights

Following World War II, President Harry Truman appointed the President's Committee on Civil Rights to analyze the status of civil rights in the United States (Jeynes, 2007; Kirk, 2020). Based on recommendations from the committee, Truman advocated for the overturn of the *separate but equal* doctrine while also adding a requirement that all federal assistance be given only in the absence of discrimination and segregation; in response, the U.S. Congress did little to achieve these ends (Kirk, 2020). Breaking with factions of his own political party, Truman made civil rights a main tenet of the Democratic Party's political platform in 1948 (Jeynes, 2007). While Truman was unsuccessful in his efforts to implement civil rights legislation after his election in 1948, Jeynes (2007) identified Truman's vision as critical for the later success in the passing of civil rights legislation as well as an avenue for federal involvement in public primary and secondary education in the United States.

With a lack of progress in passing civil rights legislation in the 1940s and early 1950s, organizations that sought change in the U.S. educational system, like the National Association for the Advancement of Colored People, instead brought civil rights issues to federal courts (Jeynes, 2007; Kirk, 2020). Following many federal court decisions favoring desegregation, the U.S. Supreme Court, in its unanimous ruling in *Brown v. Board of Education* (1954), found that the segregation of schools based on race violated the U.S. Constitution (Jeynes, 2007; Kirk, 2020). This decision generated momentum for future civil rights legislation, interpreting the constitution to provide a provision whereby the federal government could mandate the support of educating children of underrepresented groups in the United States (Jeynes, 2007).

In 1965, President Lyndon Johnson focused his administration on fighting causes of inequality and poverty, creating a program that, among other issues, centered on the education of

children (Johnson, 1966a; Johnson, 1966b; Tyack, 1974). Johnson (1966b) sought to help underrepresented groups not only "open the gates of opportunity" (p. 636) but also "move beyond opportunity to achievement" (p. 639; see also Tyack, 1974). Johnson (1966a) warned Congress that there was a "darker side" (p. 25) to education in the United States—a side where a lack of funding, for both schools and state education agencies, led to increasingly higher rates of dropouts, higher rates of unemployment, and higher costs to society (see also Tyack, 1974). Ultimately, Johnson signed the Elementary and Secondary Education Act (ESEA) in 1965. The purpose of this civil rights law was "to strengthen and improve educational quality and educational opportunities in the nation's elementary and secondary schools" (ESEA, 1965, p. 27; see also Conlan, 1981; Tyack, 1974; USDOE, n.d.). Passing ESEA was "clearly a dramatic departure from earlier education programs and proposals," authorizing more than $1 Billion in federal funding (Conlan, 1981, p. 33). This act also marked the first substantial involvement of the federal government's executive branch in public education at the elementary and secondary levels, an area that had been traditionally left to local and state governments for decisions and control (Casalaspi, 2017).

Federal Involvement in Education

The passing of ESEA introduced a pattern of increasing federal control and influence in the area of elementary and secondary public education (Casalaspi, 2017; Conlan, 1981; Groen, 2012). From 1960–1989, U.S. politicians and education experts debated whether U.S. schools were in a state of improvement or decline (Jeynes, 2007; Kessinger, 2011). In 1980, President Ronald Reagan advocated for a need to reform education in the United States and elevated the Department of Education to a cabinet-level position (Jeynes, 2007; Kessinger, 2011). Consequently, in 1983, the USDOE created the National Commission of Excellence in Education

which published a report entitled *A Nation at Risk* (Jeynes, 2007). Kessinger (2011) called this report a "watershed moment that brought the national government more dramatically into the arena of public education in the [United States]" (p. 272). This report concluded that U.S. schools were in a state of decline because standardized test scores in the United States were decreasing from 1963–1980 (Jeynes, 2007). Reagan implemented a reform program, asserting that educational programs had become too focused on the child and less focused on the school's role in society (Jeynes, 2007). During this time, the gap in standardized assessment scores between underrepresented groups and White students narrowed; however, the narrowing could have been attributable to other factors outside the reform (Jeynes, 2007). According to Jeynes (2007), Reagan's reforms were the most successful of those implemented by a Republican president from 1980–2007.

Popular public perception in the late 1980s was that reforms under Reagan had not resulted in substantial or meaningful change (Kessinger, 2011). President George H. W. Bush met with U.S. state governors to define a focus for governmental efforts to improve education (Kessinger, 2011). This meeting created a framework for implementing high national academic standards that focused on student achievement and on holding schools accountable for their results; Congress, however, rejected the framework (Kessinger, 2011). President William Clinton amended the framework to focus on a comprehensive federal role in helping all students succeed while still emphasizing state accountability; Congress used Clinton's amended framework to update and reauthorize ESEA (Groen, 2012; Kessinger, 2011). This reauthorization maintained original the focus of ESEA on disadvantaged students while also focusing federal education priorities toward student access and student literacy in the area of technology (Jeynes, 2007). Some politicians and educational experts, however, questioned whether the intent of Clinton's

framework was to create a nationally-centralized school system, a philosophy to which they were opposed (Jeynes, 2007). Furthermore, despite reforms and initiatives spanning decades and presidential terms, gaps in achievement persisted among students of underrepresented groups, such as students who were Black, students who were Hispanic, SWD, EL, students who were economically disadvantaged, etc. (Jeynes, 2007).

Shift to Multiculturalism

Shortly after the initial signing of ESEA in 1965, the United States began to see a shift in its national philosophy (Jeynes, 2007). In the 1960s, when ESEA was initially passed, the prevalent national philosophy was *Americanization*—a belief that all people in the United States should live by one set of values, cultures, and customs—that developed because of deep divides in the United States from the Civil War (Jeynes, 2007). Americanization expected immigrants to shed the values and customs of their own culture to adopt new American values (Jeynes, 2007). Starting in the 1970s, however, the United States began to see the rise of a new national philosophy—multiculturalism—in response to an increased number of immigrants that included an increased diversity among the immigrants (Banks, 1997; Jeynes, 2007). Multiculturalism was rooted in supporting inclusion and diversity (Banks, 1997; Jeynes, 2007). Federal laws supporting inclusion were passed, such as the Education for All Handicapped Children Act (1975) and the Individuals with Disabilities Act (2004), that required that children with disabilities be provided a free and appropriate education (Jeynes, 2007; Brady et al., 2020). Proponents of multiculturalism, such as Banks (1997), advocated that this philosophy should permeate all areas of the school, including the primary and secondary curriculum, to show other cultural perspectives. In response, this new and growing national philosophy caused U.S. public schools to evolve in support of inclusion and diversity (Shoffner, 2016).

While governor of Texas, George W. Bush used a multicultural approach in his educational leadership; this approach welcomed immigrants as a part of his policies and reforms (Maranto & Coppetto, 2004). Within these reforms, Bush included a system of school accountability for academic achievement of all students; however, many within his own political party opposed this philosophy (Maranto & Coppetto, 2004). After having been elected president, Bush signed NCLB in 2002 as a reauthorization of ESEA; it incorporated the ideals of multiculturalism with school accountability measures to address persistent achievement gaps in U.S. schools (Groen, 2012; Jeynes, 2007; Maranto & Coppetto, 2004; USDOE, n.d.). Schools were now accountable for the adequate yearly progress of each subgroup of students defined by NCLB toward academic achievement goals (Dee & Jacob, 2011; Groen, 2012; Jeynes, 2007). A new threat of punitive sanctions existed if schools, districts, and states did not show adequate progress toward the achievement goals of student subgroups (Dee & Jacob, 2011).

Evolution of Federal Education Policy to Accountability

No Child Left Behind marked a transformation in federal education policy from satisfying social needs to standardized testing and school accountability around annual growth goals (Groen, 2012). States were now required to identify schools that were underperforming on academic outcomes through standardized methods (Dee & Jacob, 2011; Groen, 2012; Jeynes, 2007). Among the academic achievement outcomes for which states were accountable, NCLB (2002) required that states set goals for, and report to the USDOE on, the rates at which students graduated on time (Dee & Jacob, 2011). Furthermore, states were also now required to report on the rate at which subgroups graduated on time (Dee & Jacob, 2011).

Impact on Educational Practice

By 2010, with federal legislation requiring states to report the rate at which students graduate, more than 85% of school districts offered some form of credit recovery to students (Carver et al., 2011). Many school districts across the United States turned to online learning to help students recover failed credits in order to keep them on track to graduate on time (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021; Heppen et al., 2017; Powell, Roberts, et al., 2015; Rickles et al., 2018; Viano, 2021). In 2010, Connecticut and Iowa began to require districts to use online credit interventions in an effort to increase graduation rates in those states (An Act Concerning Education Reform in Connecticut, 2010; Powell, Roberts, et al., 2015). Virginia established its own online school program in 2010, enabling students to earn high school credits through authorized online courses (Establishment of Virtual School Programs, 2010). Offering credit recovery has become increasingly popular in the United States to support the graduation of at-risk students (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Powell, Roberts, et al., 2015; Viano, 2021).

Online credit recovery may contribute to an educational opportunity gap experienced by underrepresented student groups (Dynarski, 2018; Welner & Carter, 2013). As Welner and Carter (2013) noted, “recent policy has attempted to solve problems on the cheap, looking for magic beans and silver bullets” (para. 9). When “expectations [are] minimal, … students from disadvantaged groups tend to be outperformed by their more privileged counterparts” (Welner & Carter, 2013, para. 29). Because certain groups of students, particularly those underrepresented, graduated on time at disproportionally lower rates (McFarland et al., 2020; Welner & Carter,

2013), these groups may have been more likely to participate in online credit recovery (Heinrich et al., 2019; Powell, Roberts, et al., 2015; Viano, 2021).

Educators and researchers have expressed concerns over the poor quality of online credit recovery (Heinrich et al., 2019; Powell, Roberts, et al., 2015; Viano & Henry, 2023). Powell, Roberts, et al. (2015) reported that online credit recovery

> are often computer-based software programs that are low-cost, have very low levels (if any) of teacher involvement, and require very little of students in demonstrating proficiency. [Online credit recovery programs] are used primarily because they are inexpensive, and they allow schools to say students have "passed" whether they have learned anything or not. (p. 10)

Similarly, Heinrich et al. (2019) found "that, on average, online course taking is not benefiting students or reflecting real learning, and some students may even be set back in their learning" (p. 2174). Viano and Henry (2023) identified that credit recovery interventions may be increasing graduation rates without the corresponding expected increase in knowledge that has traditionally been associated with a high school diploma. Participation in online credit recovery may, therefore, deny access for some students to participate in other, more rigorous educational opportunities, thus reinforcing a gap in educational opportunity (Dynarski, 2018; Welner & Carter, 2013).

Statement of Problem

Despite the recent increase in popularity of online credit recovery in high schools in the United States, few studies have examined student participation in online credit recovery and the subsequent outcomes associated with participation. Studies in this domain have also lacked generalizability beyond the setting of the study. Furthermore, concerns existed that online credit

recovery may have been systemically providing a poorer educational experience with associated negative outcomes to at-risk and underrepresented groups of students.

Watson et al. (2014) observed that, although much was known about how online programs are delivered to students, not much was known about the student academic outcomes following participation in such courses. Viano and Henry (2023) further noted that "hypotheses about the effectiveness of OCR [online credit recovery] have only begun to be empirically tested" (p. 4). Studies have discussed the short-term efficacy in recovering failed credit or earning credit in the next class (Hart et al., 2019; Heinrich et al., 2019; Heppen et al., 2017; Hughes et al., 2015; Stalling et al., 2016; Viano, 2021); however, a review of existing literature for online credit recovery found only three studies that explored the long-term efficacy on outcomes of on-time high school graduation (Heinrich & Darling-Aduana, 2021; Rickles et al. 2018; Viano & Henry, 2023). Findings have been inconsistent on whether credit recovery leads to higher graduation rates and have lacked generalizability outside of the studied populations (Heinrich & Darling-Aduana, 2021; Rickles et al., 2018; Viano & Henry, 2023). With schools' increased used of online learning for credit recovery (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021; Heppen et al., 2017; Powell, Roberts, et al., 2015; Rickles et al., 2018; Viano, 2021), educators and researchers have voiced concerns about the quality of the online credit recovery (Dynarski, 2018; Heinrich et al., 2018; Powell, Roberts, et al., 2015; Viano & Henry, 2023; Welner & Carter, 2013). In particular, Heinrich et al. (2019) noted that "through the lens of categorical inequality, this [online recovery] represents within-school segregation that appears to cut off some of the most academically and economically disadvantaged students from access to better quality instruction and learning opportunities" (p. 2183). Heinrich et al. were concerned that

certain student groups may be systemically participating in a credit recovery program that had negative outcomes.

The limited online credit recovery studies that have focused on long-term outcomes of on-time graduation have lacked generalizability beyond their settings (Heinrich & Darling-Aduana, 2021; Rickles et al., 2018; Viano & Henry, 2023). Further research was needed in additional regions of the United States into the student factors associated with online credit recovery participants as well as the rates at which participating students have graduated on time from high school compared to non-participants.

Purpose of the Study

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate in online credit recovery—both those who were eligible for participation and those who were never eligible. Student factors considered in this study were gender, race and ethnicity, status as EL, status as SWD, status as economically disadvantaged, status as homeless, student's high school, and student's graduation cohort.

Research Questions

Guided by the following research questions, this study examined student participation in and graduation-rate outcomes of online credit recovery in a large school division in Virginia:

1. What were factors that explained student participation in online credit recovery?
2. How much more or less likely were students who participated in online credit recovery to graduate high school on time compared to (a) the likelihood of those

who were eligible for, but did not participate in, online credit recovery and (b) the likelihood of those who were never eligible for online credit recovery?

Overview of the Study

This study was quantitative, non-experimental, and ex post facto with the purpose of (a) identifying student factors that were associated with participation in online credit recovery and (b) comparing the likelihood of on-time graduation of participants against the likelihood of nonparticipants. The study created logistic regression models to analyze explanatory student factors, participation in online credit recovery, and the likelihood of on-time graduation. The setting was a large school division in Virginia. Data were collected about the students from the participating division's Graduation Cohort 2019 and 2020 (i.e., those students who started high school in 2015–2016 or 2016–2017). Data regarding student factors were requested—gender, race and ethnicity, status as EL, status as SWD, status as economically disadvantaged, status as homeless, and school. The participating division provided all except status as economically disadvantaged. Student transcript and grade data were also collected to determine grade point average, eligibility for online credit recovery, and participation in online credit recovery. Finally, data were collected on status as an on-time graduate.

Dependent variables in this study were categorical and dichotomous; therefore, binary logistic regression models were designed to analyze collected and curated data (Orme & Combs-Orme, 2009). Research Question 1 focused on identifying factors that explained participation in online credit recovery. A binary logistic regression model was designed to identify significant coefficients associated with factors explaining participation. Research Question 2 focused on identifying how much more or less likely participants graduated on time compared to both types of nonparticipants. A binary logistic regression model was designed to generate odds ratios to

indicate the likelihood of on-time graduation given whether they were never eligible for online credit recovery, were eligible for but did not participate in online credit recovery, or participated in online credit recovery.

Theoretical and Conceptual Framework

Theoretical Framework

This study was based on the theoretical perspectives of *new institutionalism* in education (Meyer & Rowan, 2006). New institutionalism has examined how the environment of rules and regulations, particular non-local environments, have influenced not only how individuals have interacted within an institution but also how institutions have interacted with one another (Meyer & Rowan, 2006). Meyer and Rowan (2006) highlighted that "established institutions [e.g., schools, districts, etc.] become more market minded and entrepreneurial" (p. 2) in response to increased control of schools through federal and state accountability measures. Rowan (2006) also indicated that there has been support for the idea that educational institutions tend to grow isomorphically—developing into a similar structure to others through natural processes, processes designed to mimic the structure of others, or coercive processes. For example, multiple studies have shown that school districts across the United States are using online learning programs, many for credit recovery (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021; Heppen et al., 2017; Powell, Roberts, et al., 2015; Rickles et al., 2018; Viano, 2021; Wyatt, 2017).

New institutionalism provided a lens through which to view the changing landscape of education in the United States (Rowan, 2006). New institutionalism has highlighted the political and business influence of the U.S. government on K-12 education and educational reforms (Rowan, 2006). This influence has caused institutions to change and reform when recurrent

performance problems have been identified by the government (Rowan, 2006). However, this same influence has "worked to decrease Americans' historic confidence in public schools and as a consequence, unleashed at least a measure of market competition into the K-12 education sector" (Rowan, 2006, p. 16). One such recurrent problem identified in educational institutions is low on-time graduation rates of underrepresented groups of students (Atwell et al., 2019; Elbaum et al., 2014; McFarland et al., 2020; Murnane, 2013; Smith et al., 2012; Stark & Noel, 2015; Sublett & Chang, 2019). In response, businesses and economic markets, such as those promoting online credit recovery, have influenced change in K-12 schools in the United States in an attempt to solve the recurrent problem (Rowan, 2006; Mullen, 2022). Ultimately, new institutionalism identified that economic markets can create consequences for all parts of education, including the classroom (Rowan, 2006).

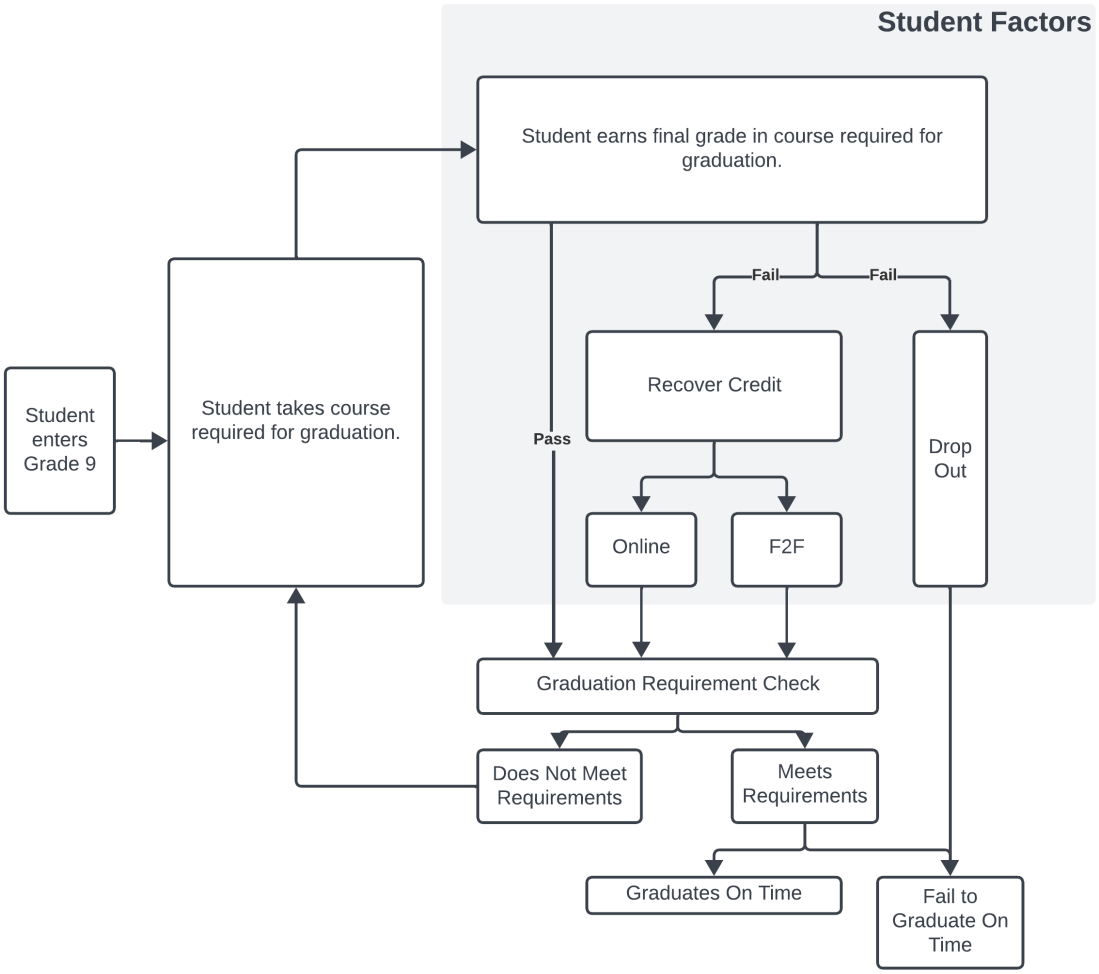
Conceptual Framework

The conceptual framework for this study highlighted the process of high school graduation and the influence of online credit recovery in helping students stay on track to graduate on time (see Figure 1). As directed by ESSA (2015), students were placed into a graduation cohort when they enter Grade 9. Upon entering a cohort, students took courses needed to graduate (Heppen et al., 2017; Rickles et al., 2018). Students who failed graduation-required classes were less likely to graduate on time—they may have dropped out, or they may have fallen behind in earning required credits (Bailey et al., 2017; Rickles et al., 2018; Uretsky, 2019; Warren et al., 2014). Students who failed a class required for graduation generally had two options to remain on track to graduate—they could have retaken the class in a face-to-face (F2F) setting or participated in online credit recovery (Hart et al., 2019; Heppen et al., 2017; Rickles et al., 2018; Viano, 2021). Once a student has met the requirements for graduation, they were

classified as graduating on time if they had achieved this status during or prior to the summer of their fourth year of high school; if not, they failed to graduate on time (ESSA, 2015).

Figure 1

Conceptual Framework of Study



Once students entered Grade 9, they began to take courses required for graduation. If a student passed the class and did not meet graduation requirements, they repeated the cycle by taking the next course. However, if they met graduation requirements, they graduated. Students

who failed the course may have recovered the credit online, recovered the credit F2F, or dropped out. Students who recovered the credit then either graduated or took the next course. Graduation was classified as *on time* if the student graduated within 4 years of entering high school. Student factors influenced how students pass classes, recover credits, or drop out.

Definition of Terms

The following terms are used in this study.

Adjusted Cohort Graduation Rate

The Adjusted Cohort Graduation Rate is defined by ESSA (2015) as:

> the fraction—the denominator of which consists of the number of students who form the original cohort of entering first-time students in Grade 9 enrolled in the high school … adjusted by adding the students who joined that cohort, after the date of the determination of the original cohort; and subtracting only those students who left that cohort, after the date of the determination of the original cohort; and the numerator of which consists of the sum of the number of students in the cohort who earned a regular high school diploma before, during, or at the conclusion of the fourth year of high school or a summer session immediately following the fourth year of high school … and shall not include any student awarded a recognized equivalent of a diploma, such as a general equivalency diploma, certificate of completion, certificate of attendance, or similar lesser credential. (pp. 292-293)

At-Risk Student

As defined by the VDOE (n.d.-f), at-risk students are "students who have a higher-than-average probability of dropping out or failing school" ("At-risk students" section; see also Darling-Aduana, 2019; Vasquez Heilig et al., 2012).

Credit Recovery

As defined by Powell, Roberts, et al. (2015):

> Credit recovery refers to a student passing and receiving credit for a course that he or she previously attempted but did not succeed in earning academic credit towards graduation. Credit recovery often differs from "first time credit" in that the students have already satisfied seat time requirements for the course in which they were unsuccessful, and can focus on earning credit based on demonstrating mastery on the content standards for the particular course. (p. 6)

Dropout

According to the Wirt et al. (2001), dropout is defined as

> both the event of leaving school before graduating and the status of an individual who is not in school and who is not a graduate. Transferring from a public to a private school, for example, is not regarded as a dropout event. A person who drops out of school may later return and graduate but is called a "dropout" at the time he or she left school. (p. 268)

The VDOE (n.d.-g) has required divisions to use exit/withdraw codes to identify students as a dropout student in Virginia (see Appendix A).

Economically Disadvantaged Student

As defined by VDOE (n.d.-f):

> A student is economically disadvantaged if the student is eligible for free/reduced meals, receives TANF [Temporary Assistance for Needy Families], or is eligible for Medicaid. If the student is identified as experiencing homelessness or becomes identified as a migrant, the student is automatically identified as economically disadvantaged and is also

> eligible for the Free and Reduced Meals Program. ("Economically disadvantaged" section)

Gaming Strategies

Acts taken by faculty or employees of schools and districts that either (a) strategically categorized certain students to prevent them from hurting achievement indicators or (b) unethically reported data to prevent students from being coded as having dropped out of school (Edwards & Mindrila, 2019; Sugarman, 2019; Vasquez Heilig et al., 2012).

Grade Point Average

A student's *grade point average* (GPA) is a numeric number that has been used by schools and districts to report a student's academic achievement in high school courses (Hansen et al., 2019; Lang, 2007). Districts decided how GPAs were calculated, and the procedure has varied from district to district (Hansen et al., 2019; Lang, 2007). Some districts have used a *weighted* GPA procedure, where certain courses are given higher point values to reflect course difficulty (Lang, 2007). Other districts have used an *unweighted* GPA procedure where there have been no adjustments based on course difficulty (Lang, 2007).

Graduation Cohort

From ESSA (2015):

> Students who form the original cohort of entering first-time students in grade 9 enrolled in the high school … adjusted by adding the students who joined that cohort, after the date of the determination of the original cohort; and subtracting only those students who left that cohort, after the date of the determination of the original cohort. (p. 290)

On-Time Graduation Rate

The four-year ACGR or a state's extended-year ACGR of a school, district, or state (ESSA, 2015). The VDOE uses a student's 4-year exit/withdraw code to determine on-time graduation rates (VDOE n.d.-g; see Appendix A).

Online Credit Recovery

Online Credit Recovery has been a program that offers credit recovery to students using online learning (Clements, Stafford, et al., 2015; Nourse, 2019; Powell, Roberts, et al., 2015).

Online Learning

According to Powell, Roberts, et al. (2015), online learning was "education in which instruction and content are delivered primarily over the internet …. The term online learning is used interchangeably with virtual learning, cyber learning, and e-learning" (p. 5).

Race and Ethnicity Categories

The USDOE has tasked schools to collect race and ethnicity information about students by asking two questions to the parents or guardians of the student (Office of the Federal Register [OFR], 2007). First, parents or guardians are asked to identify the student's ethnicity as either (a) *Hispanic or Latino* or (b) *Not Hispanic or Latino* (OFR, 2007). A student may be identified as Hispanic or Latino if the parents or guardians "trace [the student's] origin or descent to Mexico, Puerto Rico, Cuba, Central and South America, and other Spanish cultures" (OFR, 1997, p. 58787). Students are then identified as one or more races from the list of (a) American Indian or Alaska Native, (b) Asian, (c) Black or African American, (d) Native Hawaiian or Other Pacific Islander, or (e) White (OFR, 2007). Students identified as belonging to more than one race are recorded as *two or more races*; however, this is not an option for parents or guardians to choose (OFR, 2007).

In this study, the participating school division reported a student's resolved race and ethnicity which combines the ethnicity and race codes. Students were identified by the school division as American Indian or Alaska Native, Asian, Black or African American, Hispanic, Native Hawaiian or other Pacific Islander, two or more races, unknown race, or White.

Limitations and Delimitations

Limitations are aspects of the study over which the researcher does not have control and that may impact the generalizability of the findings (Roberts & Hyatt, 2018). The study was ex post facto and correlative in its design, lacking experimental controls on any variables; this lack of control prevented any direct conclusions of causality (Anderson Dannels, 2018; Creswell & Creswell, 2018). All students having taken online credit recovery courses within the same division will likely have taken them from the same online learning provider and within the context of the practices of the district's online credit recovery program (Heinrich et al., 2019); this limited generalizability to students having taken courses through a different online provider and to other school districts (Heinrich & Darling Aduana, 2021; Viano & Henry, 2023). Furthermore, divisions also determined which courses were eligible for online credit recovery—even divisions with the same online learning provider may have identified different courses available for online credit recovery (Heinrich et al., 2019; Rickles et al., 2018). Overall, there may have been limited or no generalizability to other settings. Online credit recovery was also likely one of many interventions available for at-risk students, making it difficult to isolate the impact of one intervention on the outcome of on-time graduation (Heinrich et al., 2019). Finally, the study is limited to districts that have chosen to participate and have sent data.

Delimitations are aspects of the study controlled by the researcher that exist as boundaries to the scope of the study (Roberts & Hyatt, 2018). The study was initially contained

to a purposive sample of three large school divisions in Virginia; however, only two divisions chose to participate with only one division having sent data. Students in the graduation cohorts of 2019 and 2020 were selected for the sample to control for potential effects from the Covid-19 pandemic (Viano, 2023). Intensity of online credit recovery, as measured by the number of online recovery courses taken during a student's high school career, was not be considered as a variable in the study—students were considered as participants no matter how many online credit recovery courses were taken by the student (Heinrich & Darling-Aduana, 2021).

Organization of the Study

This study is organized into five chapters. In Chapter 1, an overview of the study is provided along with a historical background, statement of the problem, purpose of the study, research questions, theoretical and conceptual frameworks, definitions of terms, limitations, and delimitations. Chapter 2 presents a review of literature and empirical research on high school graduation, implications of federal accountability structures, supporting at-risk students, and credit recovery in the United States. Chapter 3 examines the methodology of the study to include sample selection, data gathering, data analysis procedures, and a discussion of validity and reliability. Chapter 4 presents the data, computations, and analyses of the study. Finally, Chapter 5 discusses the findings, conclusions, and implications for practice, policy, and future research.

Chapter 2

Literature Review

Despite increasing graduation rates in the United States from 2001–2019, certain underrepresented groups of students, including but not limited to students with disabilities (SWD), English learner students (EL), homeless students, Black students, and Hispanic students graduated high school at a rate lower than that of their other groups (Atwell et al., 2019; Heinrich & Darling-Aduana, 2021; MacFarland et al., 2020; Sublett & Chang, 2019; Welner & Carter, 2013). Federal legislation initiatives, like the No Child Left Behind Act of 2001 (NCLB, 2002) and the Individuals with Disabilities Education Act (IDEA, 2004), were passed to hold schools, districts, and states accountable for the academic achievement of these underrepresented groups (see also Dee & Jacob, 2011). These acts also required that states track, report, and meet growth goals related to the adjusted cohort graduation rate (ACGR)—informally, the *on-time graduation rate* (OTGR)—of NCLB-defined subgroups of students (NCLB, 2001; McFarland et al., 2020). Having replaced NCLB in 2015, the Every Student Succeeds Act (ESSA) required states to create an accountability system with goals and ways to measure and report interim progress toward improving the high school graduation rate of all students.

To promote graduation goals, many districts have used multiple types of interventions, including credit recovery, to help students who are at risk of not graduating on time (Agaskar et al., 2020; Bailey et al., 2017; Carver et al., 2011; Office of the New York State Comptroller, 2013; Viano, 2021; Weiss et al., 2017). In particular, schools and districts across the United States have been using *online credit recovery* – online learning programs to help students recover failed credits in order to stay on track to graduate (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Heinrich et al., 2019; Heppen et al., 2017; Powell, Roberts, et al., 2015;

Viano, 2021). However, educators and researchers have expressed concerns about the quality of these courses (Carr, 2014; Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Heinrich et al., 2019; Powell, Roberts, et al., 2015; Viano & Henry, 2023). Studies have also found potentially negative outcomes associated with online credit recovery participation such as lower academic achievement or a diminished postsecondary earning potential (Heinrich & Cheng, 2022; Heinrich & Darling-Aduana, 2021; Rickles et al., 2018; Viano & Henry, 2023). Researchers have only recently begun to study the potential association or causal relationship between participation in online credit recovery and long-term outcomes like on-time graduation (Heinrich & Darling-Aduana, 2021; Rickles et al., 2018; Viano & Henry, 2023).

Purpose and Structure of the Literature Review

The purpose of this literature review was to examine trends in and barriers to students graduating high school on time, student participation in interventions used to support student on-time graduation, and the association of credit recovery participation with on-time graduation. Furthermore, the review sought to identify any contradictory findings of studies as well as identify opportunities for further study. Specifically, six questions guided the search process:

- What were the historical trends in high school graduation in the United States, including trends in OTGR and the influence of federal legislation?
- What barriers did students face in graduating high school, particularly on-time graduation?
- What interventions or supports did school and district leaders implement to identify and support struggling students?
- How was participation in credit recovery programs, especially those delivered online, associated with graduation rates?

- Did there exist a significant difference in the outcomes of online credit recovery on students as compared to face-to-face credit recovery (as measured by successful credit recovery, graduation, or other outcomes)?
- What ethical concerns exist given a focus of educational leaders on improving OTGR and implementing online credit recovery?

This review is divided into three sections. The first section explores the topic of high school graduation in the United States, notably the implications of graduation, the evolving measurement of OTGR, and the trends in graduation rates since 1960. The second section investigates how schools, districts, and states support students on their path to graduation, including a review of how schools use interventions, how students are identified for interventions, and how online learning is utilized in the United States. The third section focuses on literature about online credit recovery. It centers on three cases of online credit recovery in the United States, emphasizing the intervention's implementation, participation, efficacy, and association with on-time graduation.

Search Process

Peer-reviewed journals from 2011 to 2023 were primarily considered, accessed through the EBSCOhost database system and Google Scholar. Searches were conducted between August 2021 and April 2024. Research was organized into the five areas of (a) graduation trends in the United States, (b) the influence of federal legislation on school leadership and student graduation rates, (c) identification and support of students who are at risk of not graduating on time, (d) trends in online learning, and (e) online credit recovery in the United States. Articles found through this process were considered, noting important points and organizing based on themes.

Sources in the review were included because they were published articles in peer-reviewed journals, statistics reports from U.S. government agencies, or from landmark papers in an area of focus. Applicable statutes and governmental policy were also included. Literature was generally excluded if (a) the setting was outside of the United States, (b) an article did not include data-based results or findings, or (c) the scope or focus of the literature was outside of secondary schools. Exceptions to the exclusion principles were for literature that provided an important historical context or counterpoint to other literature. Key words and references of included sources were also used to find additional literature in order to focus searches into subtopics in the five areas. Greater weight was given to articles and studies from peer-reviewed journals that were more recently published.

High School Graduation

In 2019, the United States was one of only eight nations to report that over 90% of its citizens ages 25–64 years held a high school diploma or equivalent; by 2020, 95% of U.S. citizens ages 25–29 years had at least a high school diploma or its equivalent (Irwin et al., 2021). From 1970–2000, however, the rate of students graduating high school in the United States remained at approximately 80% (Murnane, 2013). Through NCLB (2002), Congress directed the U.S. Secretary of Education to identify and disseminate information about effective programs that could increase secondary school graduation rates in U.S. high schools. Since 2001, graduation rates have steadily increased in the United States (Irwin et al., 2021; McFarland et al., 2020; Welner & Carter, 2013). Furthermore, the overall OTGR increased each year in the United States from 79% in 2011 to 86% in 2019 (National Center for Education Statistics, 2021b).

Despite these improvements, some underrepresented groups of students had OTGRs that were lower than the national average (Atwell et al., 2019; Elbaum et al., 2014; McFarland et al.,

2020; Murnane, 2013; Smith et al., 2012; Stark & Noel, 2015; Sublett & Chang, 2019; Welner & Carter, 2013). In 2019, American Indian/Alaska Native students (74%), Black students (80%), and Hispanic students (82%) all graduated below the national OTGR of 86% (Irwin et al., 2021). Similarly, in 2017, economically-disadvantaged students (78%), homeless students (64%), EL (66%), and SWD (67%) all lagged behind the national OTGR of 85% (Atwell et al., 2019).

Implications of High School Graduation

High school graduation has remained an important personal and social milestone in the United States (Qu et al., 2016). Studies have highlighted several personal benefits for students who graduate high school (Bureau of Labor Statistics, 2015; Murnane, 2013; Qu et al., 2016). Since 1979, high school graduates have consistently earned higher wages and salaries than students who drop out of school (Murnane, 2013). In 2014, high school graduates with no college annually made over $9,000 more than people without a high school diploma (Bureau of Labor Statistics, 2015). By 2023, that difference increased to more than $10,000; for high school graduates with some college or an associate degree, the difference was more than $17,000 annually (Bureau of Labor Statistics, 2024). In 2023, high school graduates with a bachelor's degree or higher made more, on average, more than $46,000 annually than a person without a high school diploma (Bureau of Labor Statistics, 2024). High school graduates also generally break fewer laws and have decreased healthcare needs as compared to those who did not graduate (Qu et al., 2016).

Correspondingly, there have been several societal benefits to improving OTGRs (Bailey et al., 2020; Qu et al., 2016; Vining & Weimer, 2019). It has been costing thousands of dollars annually to educate each student in public schools, and students who have been retained in a grade have presented significant financial burdens on school districts (Bailey et al., 2020;

Marchbanks et al., 2014; Rumberger et al., 2016). Specifically, Bailey et al. (2020) found that a student who had a disability could have costed a district almost twice what it annually costs to have continued to educate a student without disabilities because of lower required student-to-staff ratios. From a community lens, societal economic benefits to high school graduation have included greater employee productivity, lower healthcare costs, less crime, less need for public assistance, and lower costs of education (Qu et al., 2016). Qu et al. (2016) also found that community investments in interventions to support OTGR have been less expensive than the societal costs needed to support those without a high school diploma. These societal costs have come from those who did not complete high school and are involved in increased rates of crime or increased dependency on government programs like welfare (Qu et al., 2016). When considering the cost associated with interventions designed to help students graduate, the cost benefit has increased when the intervention was given to students still in school as opposed to interventions provided to those who have already dropped out of school (Qu et al., 2016). Vining and Weimer (2019) estimated that each additional 100 high school graduates have added a societal value of approximately $32 million. Therefore, graduating high school—and graduating on time—has been substantially important to the interests of students, schools, school districts, governments, and communities (Qu et al., 2016).

Measuring On-Time Graduation

While there have been many different ways to calculate the U.S. high school graduation rate, NCLB (2002) required that states use an ACGR to calculate, report, and track OTGR for public high schools. Similarly, ESSA (2015) continued to require states to have accountability systems with goals and methods to measure interim progress toward improving both achievement and the OTGR of all students from high school. Like NCLB, ESSA also used

ACGR as its primary means of calculating the on-time graduation (ESSA, 2015; Schultz, 2017). One priority of ESSA, however, was providing states with more flexibility to show achievement and school accountability while maintaining federal accountability (Shoffner, 2016).

To provide that flexibility, ESSA (2015) allowed states to create their own additional metrics to measure and set goals for OTGR. By 2018, 35 states used a method other than the ACGR to calculate OTGR (Kostyo et al., 2018). For example, the Virginia Department of Education (VDOE, n.d.-e) used a *Graduation and Completion Index* to determine OTGR for identifying a school's accreditation status or for identifying schools in need of support and improvement. This index also accounted for students who graduated or completed high school in alternative ways, such as earning a general equivalency diploma or other certificate given for successful completion of high school, in a way that the ACGR did not (VDOE, 2011).

Graduation Trends since 1960

From 1960–2000, Joo and Kim (2014) estimated the OTGR in the United States to be under 70%, decreasing slightly over that time period. Since the implementation of NCLB, graduation rates in U.S. public high schools have steadily increased (Irwin et al., 2021; McFarland et al., 2020; Warner & Carter, 2013). In 2011, the U.S. OTGR had improved to 79% (McFarland et al., 2020); however, 15 states still reported an overall graduation rate below 75% (Atwell et al., 2019). Graduation rates continued to improve through 2017 with the national OTGR at 85% (McFarland et al., 2020) and with only one state reporting an overall graduation rate below 75% (Atwell et al., 2019). This improvement accounted for more than 3.5 million additional graduates than would have graduated if the national OTGR remained at the same level as it was in 2000 (Atwell et al., 2019).

Despite these positive trends, certain underrepresented groups of students, including but not limited to SWD, homeless students, and EL, have historically graduated at rates lower than the national OTGR (Atwell et al., 2019; Elbaum et al., 2014; McFarland et al., 2020; Murnane, 2013; Smith et al., 2012; Stark & Noel, 2015; Sublett & Chang, 2019; Warner & Carter, 2013). Similarly, certain races and ethnicities of students, such as Black students and Hispanic students, have also lagged behind the U.S. OTGR (Atwell et al., 2019; McFarland et al., 2020; Warner & Carter, 2013). Furthermore, the issue of not graduating on time has been disproportionately concentrated in approximately 13% of public high schools in the United States (Atwell et al., 2019; Murnane, 2013).

Races and Ethnicities. In 2019, there were 50.7 million students in public schools in the United States (Irwin, 2021). Two groups of students, Black students and White students, formed smaller proportions of public-school students in 2019 compared to 2009 (Irwin, 2021). White students comprised 54% of students in 2009, decreasing to 47% in 2019; Black students comprised 17% of students in 2009, decreasing to 15% in 2019 (Irwin et al., 2021). Hispanic students were the only group to form a larger proportion of students in the United States in 2019 compared to 2009—27% of students in 2019 compared to 22% in 2009 (Irwin et al., 2021). For the final three races and ethnicities, their proportions remained constant—Asian/Pacific Islanders comprised 5% of the students, two or more races comprised 4%, and American Indian/Alaska Native comprised the remaining 1% (Irwin et al., 2021).

McFarland et al. (2020) found that only two races or ethnicities— Asian/Pacific Islander students and White students—graduated at rates above the national OTGR of 85% in 2017. Below the national OTGR that year were Hispanic students (80%), Black students (78%), and American Indian/Alaska Native (72%; McFarland et al., 2020). Atwell et al. (2019) reported that

Black and Hispanic students continued to be disproportionately represented in the number of dropout students in the United States as of 2017. Furthermore, Black and Hispanic students were also more likely than students of other races and ethnicities to be retained in a grade, most often Grades 1 or 9 (Warren et al., 2014).

Dating back to the early 1960s, Black and Hispanic students in the United States were significantly more likely to drop out of school and significantly less likely to graduate high school by the age of 18 as compared to White students (Joo & Kim, 2014). From 2001–2017, the OTGR for Black and Hispanic students both increased by over 22 percentage points (McFarland et al., 2020). In 2017, Hispanic students became the third race and ethnicity group in the United States to cross the 80% OTGR threshold; however, this rate was still 9 percentage points below the rate of White students (McFarland et al., 2020). The OTGR for Black students reached 78% in 2017; similarly, this rate was 11 percentage points below the OTGR of White students (McFarland et al., 2020). McFarland et al. (2020) reported that 33 states had statistically-significant gaps in OTGR between Black and White students in 2017. In 2019, Black students became the fourth race and ethnicity group to break the 80% graduation rate threshold (Irwin et al., 2021).

Black and Hispanic students also disproportionately attended schools with the lowest graduation rates (Atwell et al., 2019; Murnane, 2013; Warner & Carter, 2013). In 2008, a majority of dropouts came from only 14% of high schools in the United States (Murnane, 2013). Murnane (2013) also found that over 50% of these schools were located in an urban setting, and approximately 33% of the schools were located in a rural setting. By 2017, Atwell et al. (2019) reported that the number of high schools with an OTGR of 67% or less had fallen to 13% of schools in the United States. These schools enrolled 7% of students nationally, but they

accounted for approximately 31% of students in the United States who did not graduate on time (Atwell et al., 2019). Atwell et al. also reported that nearly 77% of these schools had already been identified by their states for support and improvement through provisions of ESSA. In four states—Arizona, Colorado, Florida, and New Mexico—20% or more of high schools were schools with low graduation rates in 2017 (Atwell et al., 2019). In seven states that same year, at least 25% of students not graduating on time came from a low-graduation-rate school (Atwell et al., 2019).

English Learners. The number of EL in the United States increased by approximately 5 million students from 2009–2019, comprising over 10% of public-school students nationally by 2019 (Irwin et al., 2021). These students were mainly concentrated in 10 states where the population of EL was more than 10% (Irwin et al., 2021). In particular, nearly 20% of students in California and Texas were identified as EL in 2019 (Irwin et al., 2021). In contrast, five states—Montana, New Hampshire, Vermont, West Virginia, and Wyoming—had EL populations below 3% (Irwin et al., 2021).

Students who are learning English graduated at a rate lower than the national average in the 2010s (Atwell et al., 2019; McFarland et al., 2020). Atwell et al. (2019) found that there was a national gap of 53 percentage points in OTGR between EL and non-El students in 2017. In New York, only 64% of EL who entered New York City public schools in Grade 5 or Grade 6 graduated high school on time in 2013 (Kieffer & Parker, 2017). In Arizona, students classified as EL or had been previously classified as an EL were significantly less likely to graduate on time in 2014 (Huang et al., 2016). With the exception of students who are homeless, EL have had the lowest OTGR of any reported category of student (Atwell et al., 2019). Notably, in 2017,

despite the nation OTGR improving, the OTGR of EL did not increase, but decreased, in 19 states (Atwell et al., 2019). Fifteen states reported an EL OTGR below 60% (Atwell et al., 2019).

Students who are Economically Disadvantaged. States have had different procedures for classifying students as economically disadvantaged (McFarland et al., 2020). For example, states may have classified a student as economically disadvantaged only at the start, only at the end, or at any time during a student's high school career (McFarland et al., 2020). Based on state reporting, economically-disadvantaged students accounted for more than 47% of the 2017 graduation cohort (Atwell et al., 2019).

Nearly two-thirds of the students in the United States not graduating on time in 2017 were considered economically disadvantaged (Atwell et al., 2019). From 2011–2017, the OTGR of these students increased from 70% to 78%, seven percentage points below the national average (Atwell et al., 2019; McFarland et al., 2020). Five states—Arkansas, Kentucky, South Carolina, Texas, and West Virginia—graduated economically-disadvantaged students at a rate higher than the overall national OTGR (Atwell et al., 2019). In that same year, Atwell et al. (2019) also reported that 10 states had a gap of at least 20 percentage points in OTGR between economically-disadvantaged students and non-economically-disadvantaged students—Wyoming (24 percentage points), Minnesota (24 percentage points), South Dakota (24 percentage points), Michigan (21 percentage points), and Colorado (20 percentage points). Thirteen states saw such gaps widen from 2011 to 2017 (Atwell et al., 2019). Economically-disadvantaged students in the United States were over-represented in schools with low graduation rates through 2017 (Atwell et al., 2019). Of the public schools in the United States with an OTGR below 67% in 2017, over half of the students attending these schools were economically disadvantaged (Atwell et al., 2019).

Students who are Homeless. States reported that students who are homeless, such as those students without permanent housing or those staying with another family because of an economic hardship, had the lowest OTGR of any single reported student group in the United States through 2017 (Atwell et al., 2019). Graduation trends for this student group have been generally unknown because, prior to 2018, neither NCLB nor ESSA required states to report the rate at which homeless students graduated (Atwell et al., 2019). In 2019, there were approximately 150,000 homeless students in the national graduation cohort as reported by the U.S. Department of Education ED Data Express (n.d.).

Atwell et al. (2019) were able to report on 26 states who voluntarily shared their 2017 OTGR for students who are homeless. Of those 26 states, only one – Delaware – reported an OTGR for homeless students above 80% (Atwell et al., 2019). On the other end, for students who were homeless, one state reported an OTGR below 50%; eight states reported an OTGR between 50% and 60%; and, 10 states reported an OTGR between 60% and 70% (Atwell et al., 2019).

Students who have a Disability. In 2017, there were over seven million SWD in the United States—approximately one million more students than the total sum of homeless students and EL students (Irwin et al., 2021; National Center for Education Statistics, 2019). Furthermore, according to Irwin et al. (2021), the number of students identified as having a disability increased in the United States since 2011. By 2020, the number of students identified as having a disability was 14% (Irwin et al., 2021).

Students identified as having a disability have been less likely to graduate on time than students without disabilities (Elbaum et al., 2014; McFarland et al., 2020; Stark & Noel, 2015; Smith et al., 2012; Sublett & Chang, 2019). While still below national overall averages and

averages for students without disabilities, rates of graduation and high school completion for SWD have generally increased since 2002 (Elbaum et al., 2014; McFarland et al., 2020; Stark & Noel, 2015). The OTGR for SWD was 59% in 2012, rising to 67% in 2017 (Atwell et al., 2019; McFarland et al., 2020). The highest OTGR for SWD in 2017 came from Arkansas at 84%, and the lowest came from Mississippi at 36% (Atwell et al., 2019; McFarland et al., 2020). However, both Atwell et al. (2019) and McFarland et al. (2020) encouraged caution when comparing OTGR data for SWD between states given varied diploma types and disability identification procedures among states. Some states have also increased graduation rates for SWD by changing graduation requirements—Nevada, for example, changed graduation requirements and then reported a 7 percentage point increase in OTGR in 2017 compared to 2016 (Atwell et al., 2019). Some states have also retroactively awarded diplomas when graduation requirements were adjusted; however, these diplomas were not retroactively included in a state's reported OTGR (Atwell et al., 2019).

A student's disability itself has also been a predictor of the length of time needed to graduate (Schifter, 2011; Smith et al., 2012). More students were classified as having a specific learning disability (SLD) in the United States than any other disability type, comprising approximately one-third of all SWD (Irwin et al., 2021). Schifter (2011) found that SLD students were most likely to graduate on time of all disability categories. Smith et al. (2012), however, found SLD students to be fourth most likely to graduate of all disability types, behind students with visual impairments, hearing impairments, and orthopedic impairments. Smith et al. also found that students with autism graduated at a rate comparable to those with SLD. Students who were identified both as SWD and economically disadvantaged tended to graduate on time at a

lower rate than those SWD who were not identified as economically disadvantaged (Elbaum et al., 2014).

Ethical Implications of Federal Accountability

The implementation of NCLB caused instability in schools by shifting the focus of the school leader from instructional leadership to student achievement management (Gosnell-Lamb et al., 2013; Vasquez Heilig et al., 2012). In theory, principals and school leaders were now focused on managing change and on the principal's ultimate accountability for academic achievement (Crum & Sherman, 2008), and this new focus introduced a new need for school leaders to receive different training and professional development (Pepper, 2010). In practice, NCLB introduced a new stress on school leadership that resulted in increased turnover of school principals (Mitani, 2018).

Because of the accountability and high-stakes testing necessary to satisfy the demands of NCLB, educational leaders and teachers focused on short-term, rather than long-term, results (Dee & Jacob, 2011; Edwards & Mindrila, 2019; Jennings & Bearak, 2014; Vasquez Heilig et al., 2012). Tasked with helping students pass tests now required for academic achievement accountability and student graduation, many schools implemented strategies such as narrowly-focused instruction around standards-based assessments (Choi, 2011; Dee & Jacob, 2011; Edwards & Mindrila, 2019; Jennings & Bearak, 2014). While these strategies resulted in improved student achievement outcomes (Dee & Jacob, 2011; Jennings & Bearak, 2014), the positive achievement may have been more related to teachers anticipating the test than student learning outcomes (Jennings & Bearak, 2014). Schools leaders used NCLB to refocus instruction and allocate resources to support at-risk students (Dee & Jacob, 2011). Dee and Jacob (2011) also identified several studies that pointed to accountability measures positively impacting

student achievement, and assessment results from the National Assessment of Educational Progress showed a significant increase in Grade 4 math achievement scores across the United States. In spite of positive outcomes, the accountability measures of NCLB led to cultures of fear in schools and districts (Vasquez Heilig et al., 2012).

Federal accountability measures "led many educators to view students as liabilities" (Vasquez Heilig et al., 2012, p. 572), focusing on strategic methods to probe and scrutinize data in an effort to circumvent reporting requirements (Edwards & Mindrila, 2019). Many educational leaders used these *gaming strategies*—procedures designed to enhance achievement data reported to the state and federal government—to give the appearance of increased graduation rates and academic achievement outcomes (Edwards & Mindrila, 2019; Sugarman, 2019; Vasquez Heilig et al., 2012). Some school leaders also used unethical data reporting strategies, such as purging student data or fabricating withdrawal information (Edwards & Mindrila, 2019).

Schools and districts were incentivized to avoid enrolling students who may have struggled to graduate on time, such as students who were EL or students with significant gaps in their education (Sugarman, 2019). Similarly, some students in Texas who were at risk of not meeting accountability standards for their school were encouraged by school leaders to drop out or to transfer to other schools (Vasquez Heilig et al., 2012; Brown, 2013). From 2005–2011, one district in Texas, under direction of the superintendent and high school principals, falsified transcripts, reclassified students to avoid achievement assessments, removed the EL classification for students who still qualified, and manipulated attendance data across seven high schools; school officials who refused to file changes were re-assigned to other buildings (Brown, 2013). The district also used credit recovery to help students quickly earn failed credit in

thousands of courses, violating district policy and state law to manipulate graduation rates (Brown, 2013).

Likewise, in Georgia, some districts either falsified withdrawal forms for students who dropped out (in an effort to have them not count as a dropout), or they encouraged parents to falsely indicate on withdrawal paperwork an intention to home school the student—even if the parent did not so intend—so that the school could classify the student as a transfer as opposed to a dropout (Edwards & Mindrila, 2019). In Virginia, the VDOE (2018) found Richmond City Public Schools (2019) to have incorrectly identified students as eligible for graduation. The VDOE identified issues of counting credits toward graduation for courses not formally approved, inappropriately awarding the number of credits for a course to include awarding credit for courses that carried no credit, and awarding credits toward graduation for middle school courses (see also Richmond City Public Schools, 2019).

The District of Columbia Public Schools also used online credit recovery as a gaming strategy to increase on-time graduation rates (Alvarez & Marsal, 2018). Alvarez and Marsal (2018) found that most high schools in District of Columbia Public Schools (DCPS) inappropriately used credit recovery, both online and face-to-face (F2F), to award course credit that was against district policy or program requirements. Some students were enrolled in credit recovery for first-time credit, and some schools created their own credit recovery programs that were not aligned with DCPS credit recovery practices and DCPS grading policies. Alvarez and Marsal also found that attendance policies related to grading were often ignored, a lack of oversight by district leaders when high school leaders violated DCPS policies, and most high schools had implemented a culture of passing students that placed awarding credit over academic

standards and rigor. In 2017, 34% of students who graduated from a DCPS high school did so with at least one violation of policy (Alvarez & Marsal, 2018).

Gaming strategies have also been used by state agencies (Schultz, 2017). In 2011, the Alabama State Department of Education (ALSDE) reported an OTGR of 72%, seven points below the national OTGR average (Schultz, 2017). By 2014, the ALSDE reported an increased OTGR of 14 percentage points to 86%, four points above the national OTGR that year (Schultz, 2017). Through an audit in 2017, the U.S. Department of Education found that the ALSDE (a) misreported the 2014 OTGR data by including students who did not earn a regular diploma and (b) failed to provide "internal control … that [the] reported graduation rates were accurate and complete" (Schultz, 2017, p. 5). Furthermore, the audit found that ALSDE reported an inflated OTGR by excluding students from the 2014 cohort (Schultz, 2017).

According to Dynarski (2018), this sudden social movement to measure student achievement and graduation rates exemplified the concerns and consequences of Campbell's Law wherein attempts to quantify and measure a social process will corrupt it from achieving the desired outcome (see also Campbell, 1976). Campbell (1976) stated that "the more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor" (p. 49). For a school-level example of such a distortion and corruption, Powell (2020) found that a school-based credit recovery program ultimately exacerbated and magnified the racial disparities and inequities for which it was initially implemented to address. Ultimately, Black students began to reject the help offered by the credit recovery program because of negative interactions with teachers outside of the program; however, White students did not have those same negative interactions and benefitted from the program (Powell, 2020).

Viano and Henry (2023) also questioned whether online credit recovery had improved graduation rates without providing the corresponding increase in knowledge that normally would have been gained by a traditional high school graduate (see also Heinrich & Cheng, 2022). To Dynarski, the gaming strategies of educational leaders, evident only since the implementation of NCLB, have demonstrated the effects of Campbell's Law where federal accountability has corrupted the initial positive intentions of increasing student achievement and on-time graduation. Dynarski, among others, questioned whether the increases of OTGR since 2001 may have then been artificial or inaccurate (see also Alvarez & Marsal, 2018; Brown, 2013; Edwards & Mindrila, 2019; Schultz, 2017; VDOE, 2018).

Supporting Students to Graduation

Despite the upward trend of OTGR from 2001–2019, many students have still struggled to graduate (Gubbels et al., 2019; Irwin et al., 2021; McFarland et al., 2020; Rickles et al., 2018). Identifying students who are at risk of not graduating on time (i.e., at-risk students) has been an important concern of educational and community leaders (Gubbels et al., 2019; Qu et al., 2016; Weiss et al., 2017). Educational leaders have used existing student data to identify these at-risk students because not graduating on time has been, generally, a known and studied process (Agaskar et al., 2020; Bruce et al., 2011; Dupéré et al., 2015; Dupéré et al., 2021). At the same time, some at-risk students have had unique learning needs that were best satisfied through online coursework or non-traditional methods (Heinrich et al., 2019; Powell, Watson, et al., 2015). Online courses were able to serve students who needed either advanced courses not taught in the student's traditional school or a repetition of a course to recover credits needed for graduation (Ahn & McEachin, 2017; Barnett, 2016; Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Holian et al., 2014). Online courses have also helped students to complete

courses needed for graduation when students struggled in traditional settings or needed more courses to graduate on time than would be possible in traditional settings (Heinrich et al., 2019).

Identifying At-Risk Students

Schools and districts across the United States have used early warning systems (EWS) that take readily-available student factors to identify students at-risk of dropping out of school (Bruce et al., 2011; Davis et al., 2019; Faria et al., 2017; Hazel et al., 2014; Mac Iver et al., 2019; Sepanik et al., 2021). Oregon, for example, committed funding for its districts to identify at-risk students in Grades 8-10 (Oregon Department of Education, 2021). This approach has been seen as necessary to account for many students entering high school with immediate and specific needs (Hazel et al., 2014).

An EWS uses student factors—behaviors. traits, or characteristics—in the areas of academic success (e.g., grades and test scores), engagement with school (e.g., attendance and behavior), and development of positive educational goals or expectations to identify at-risk students (Benner et al., 2021; Davis et al., 2019). Multiple studies have found that the factor of student attendance at school was directly related to a student's on-time graduation (Hoover & Cozzens, 2016; Liu et al., 2021; Mac Iver & Messel, 2013; Uretsky, 2019). Studies have also found that students who receive disciplinary suspensions have been also more likely to drop out of high school (Gubbels et al., 2019; Hoover & Cozzens, 2016; Lee et al., 2011).

Despite its popularity, EWSs enacted by schools and districts have not necessarily created an immediate positive impact on student academic progress toward on-time graduation (Faria et al., 2017; Sepanik et al., 2021). Faria et al. (2017) conducted a randomized study in 73 schools in the Midwest United States who used an EWS, finding that an EWS did not have an

immediate impact on students earning credits. However, Faria et al. indicated that EWSs showed promise in addressing issues with school absences and course failure.

The documented reliability of an EWS has been varied (Davis et al., 2019; Faria et al., 2017; Mac Iver et al., 2019; Sepanik et al., 2021). Two studies found that only one EWS factor—attendance—reliably and correctly identified at-risk students (Mac Iver, 2019; Sepanik et al., 2021). Two other studies found that two EWS factors—attendance and academic course success—reliably identified at-risk students (Davis et al., 2019; Mac Iver & Messel, 2013). Gubbels et al. (2019) conducted a meta-analysis of 75 studies on student drop out, finding 23 factors that were significantly associated with students dropping out of school primarily in the areas of problems at or with school, physical and mental problems, anti-social behavior, parenting problems and difficulties, family structure problems, characteristics of the school, and peer group characteristics.

Factors used in an EWS have not perfectly identified all students who are at risk of dropping out of school (Benner et al., 2021; Gubbels et al., 2019). Benner et al. (2021) found hundreds of students who dropped out of high school despite high grades, high educational expectations, future educational plans, and high levels of attendance. Students also have tended to grow and change during a school year; the profile of at-risk Grade 9 students at the start of a year may differ from the profile of at-risk Grade 9 students at the conclusion of the school year (Hazel et al., 2014).

There were several additional factors that have contributed to a student being at risk that may not have been readily quantifiable for use in an EWS (Benner et al., 2021; Dupéré et al., 2015; Dupéré et al., 2021; Gubbels at el., 2019; Uretsky, 2019). Dupéré et al. (2021) indicated that not only were students less likely to graduate when they see dropout behaviors in their

school or community, but also that this risk increased when a student has seen it recently or has multiple people close to them, such as friends, romantic partners, or family members, who had dropped out. Benner et al. (2021) identified that students who engaged in sexual intercourse or alcohol use during high school were more likely to fall off track academically. Similarly, students who had a family member added, removed, or exit from the family fell off track academically (Benner et al., 2021). In contrast, Benner et al. found that factors such as starting a romantic relationship, smoking marijuana or tobacco, or changing schools did not decrease a student's likelihood of on-time graduation.

Interventions for At-Risk Students

Uretsky (2019) found that student promotion to Grade 10 by the end of their first year in high school doubled a student's chance to graduate on time. In a district where standardized end-of-course tests are given, students who passed their first high school standardized assessment by the end of their Grade 9 year quadrupled their likelihood of graduating on time (Uretsky, 2019). Students in Grade 9 were also more likely to be retained than in any other grade in high school (Warren et al., 2014).

To support students in staying on track academically, and therefore on track for on-time graduation, there has been a need for interventions to be implemented early in a student's high school career (Hazel et al., 2014). Conversely, there has also been a concern that these interventions, if enacted in the early high school years, may have had a diminished impact on future outcomes that are years away, such as graduation (Bailey et al., 2017). Bailey et al. (2020) called this phenomenon *fade out* and indicated that it has been expected of interventions used in schools (Bailey et al., 2020). However, even with diminished returns from fade out, Bailey et al.

(2020) found that any intervention that impacted important outcomes, like on-time graduation, had value.

Impacts of Interventions. Schools and districts across the United States have used a variety of interventions to support at-risk students in both academic and non-academic areas (Agaskar et al, 2020; Bailey et al., 2017; Weiss et al., 2017). Families have preferred interventions such as after-school programs, services to help students with mental health, and services to help students with substance abuse (Agaskar et al., 2020). Agaskar et al. (2020) also found that at-risk students, contrastingly, have preferred interventions such as career preparedness programs, sports-related activities, and access to quality teachers. School-based mentoring has also been a popular and effective intervention (Heppen et al., 2018; Weiss et al., 2017). Weiss et al. (2017) found that mentoring programs that lead to positive relationships with adults increased the chances of a student graduating on time.

Despite good intentions, some interventions may have also led to negative impacts on future outcomes of participating students (Bailey et al., 2017). Furthermore, there has not always been a significant association between interventions and a student's on-time graduation (Heppen et al., 2018). Some interventions may have also led to future negative interactions with the juvenile justice system, participation in academic programs or courses with lower expectations, or lower student academic achievement (Bailey et al., 2017). Concerns with online credit recovery have included the participation in academic programs or courses with lower expectations (Heinrich et al, 2019; Heppen et al., 2017; Viano & Henry, 2023) and lower student academic achievement (Heppen et al., 2017; Powell, Roberts, et al., 2015; Viano & Henry, 2023).

Credit Recovery as an Intervention. By 2009, over 85% of school districts in the United States offered some form of credit recovery program as an intervention to address academic course success concerns (Carver et al., 2011). School districts have also been developing credit recovery options in online settings (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Hart et al., 2019; Hughes et al., 2015; Heinrich et al., 2019; Heppen et al., 2017; Viano, 2021). Some schools and school districts offered online courses or credit recovery based on state law or policy requirement (An Act Concerning Education Reform in Connecticut, 2010; Frazelle, 2016; Hart et al., 2019; Stallings et al., 2016). With the COVID-19 pandemic, schools in the United States also had new reason for such courses, and they transitioned quickly to online methods in response to restricting in-person instruction (Irwin et al., 2021). Many districts have provided multiple options for students to recover credits, both through online courses and through F2F courses (Hart et al., 2019; Heppen et al., 2017; Hughes et al., 2015; Office of the New York State Comptroller, 2013).

Researchers and educators have expressed concerns about the quality of these online courses (Carr, 2014; Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Office of the New York State Comptroller, 2013; Powell, Roberts, et al., 2015). Three studies found that taking an online class by any student was associated with a lower OTGR when compared to a student who did not take an online course (Hart et al., 2019; Heinrich & Darling-Aduana, 2021; Sublett & Chang, 2019). Organizations and researchers outside of the U.S. public school system, like the National Collegiate Athletic Association, also have expressed concerns about online courses being of lower quality, less engaging, or harder than traditional course options (Carr, 2014).

While online courses may have been growing in popularity, not all districts in the United States have been prepared to offer online learning options (Heinrich et al., 2019; Holian et al., 2014). Some districts have not implemented online learning programs because they did not have the technological capacity required to implement such programs (Holian et al., 2014; Powell, Watson, et al., 2015). Lack of school resources, such as financial resources, can be another reason why schools have not implemented online learning (Heinrich et al., 2019; Powell, Watson, et al., 2015). Some students have also lacked the resources at home, such as internet access, to connect with online courses (González-Betancor, 2021; Irwin et al., 2021).

There has also been limited research on the efficacy and effectiveness of online credit recovery interventions in supporting at-risk students graduate on time (Rickles et al., 2018; Viano & Henry, 2023). As Viano and Henry noted in 2023, "hypotheses about the effectiveness of OCR [online credit recovery] have only begun to be empirically tested" (p. 4). Additionally, Dynarski (2018) expressed concern that credit recovery as an intervention may have been aiding to an artificial inflation of the reported OTGR in the United States.

Examining Online Credit Recovery

Schools have been increasingly using online credit recovery to support at-risk students (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Hart et al., 2019; Heinrich et al., 2019; Heppen et al., 2017; Stallings et al., 2016; Viano, 2021). While some students taking online credit recovery courses may have been considered at risk, not all students who use this intervention were at risk of not graduating on time (Clements, Pazzaglia, et al., 2015; Clements, Stafford, et al., 2015; Powell, Roberts, et al., 2015). In Virginia, 74% of school divisions offered some version of an online credit recovery program to students by 2016 (Wyatt, 2017). Wyatt

(2017) also found that graduation rates in those same divisions improved, on average, by 10 percentage points from 2008–2016.

Online Credit Recovery Providers

Some state governments have also mandated the implementation of online credit recovery within schools (An Act Concerning Education Reform in Connecticut, 2010; Powell, Roberts, et al., 2015). In 2010, the state of Connecticut passed legislation requiring any district with a dropout rate of 8% or higher to implement an online credit recovery program for at-risk students (An Act Concerning Education Reform in Connecticut, 2010). In that same year, Virginia passed legislation, the Establishment of Virtual School Programs (2010), requiring that online providers of these programs meet minimum standards. Unlike Connecticut's online course legislation, Virginia's legislation did not mandate the use of an online course provider in any school division if the division did not offer online courses (An Act Concerning Education Reform in Connecticut, 2010; Establishment of Virtual School Programs, 2010).

Virginia's legislation mandated that the VDOE to create model policies and procedures for local school divisions to select, monitor, and remove such online providers (Establishment of Virtual School Programs, 2010). Many different providers of online credit recovery have existed in the United States (Powell, Roberts, et al., 2015), and over 20 providers have been approved by the VDOE since 2011 (VDOE, n.d.-a; Wyatt, 2017). In 2016, Wyatt (2017) found that Apex Learning was the most popular provider in Virginia, selected by 17 divisions—a majority of the school divisions in Virginia at that time. Five other providers—Edgenuity (7), OdysseyWare (7), Edmentum (6), Compass Learning (4), and GradPoint (2)—had also been selected by multiple divisions (Wyatt, 2017). By 2024, there were 24 approved multidivision online providers in Virginia (VDOE, n.d.-a). In 2024, a total of 58 divisions used Imagine Edgenuity; furthermore,

four providers—Imagine Edgenuity (58), Edmentum EdOptions Academy (33), Apex Learning (28), and Stride K12 (26)—each served more divisions than Apex Learning served in 2016 (VDOE, n.d.-a; Wyatt, 2017). Eleven multidivision online providers served multiple school divisions in 2024, and all but three offered online credit recovery (VDOE, n.d.-a). For more information regarding multidivision online providers in Virginia, see Appendix B.

Some states have also become providers of online learning and credit recovery (Frazelle, 2016; Powell, Roberts, et al., 2015; Stallings et al., 2016). State-managed virtual public schools or academies have eased barriers for districts, schools, and students to access online courses for credit recovery and curriculum acceleration (Frazelle, 2016; Powell, Roberts, et al., 2015; Stallings et al., 2016). Frazelle (2016) identified that the most successful academies established a consistent program structure, provided instructional support, built relationships with open communication, and developed data tools to monitor and communicate student progress.

While all of these schools, districts, and states may call these programs online credit recovery, there are many different models, methods, and providers (Heppen et al., 2017; Powell, Roberts, et al., 2015). These variations have made studying online credit recovery difficult to generalize to other programs outside of the setting (Heinrich & Darling-Aduana, 2021; Viano & Henry, 2023). This concern also applied to quasi-experimental studies that used randomization (Heppen et al., 2017; Rickles et al., 2018).

Benefits and Concerns of Online Credit Recovery

Online credit recovery was designed to help students who failed a class to earn that credit, and it was found by several studies to be beneficial for students on their path to graduation (Heinrich & Darling-Aduana, 2021; Pettyjohn & LaFrance, 2014; Rickles et al., 2018; Stallings et al., 2016; Viano & Henry, 2023). Some studies have also shown that online credit recovery

has been more effective than F2F recovery options in helping students successfully recover failed credits (Hart et al., 2019; Pettyjohn & LaFrance, 2014; Stallings et al., 2016; Viano, 2021). For SWD who failed a course, Viano (2021) found that they were significantly more likely to recover the credit if they used online—rather than F2F—recovery: "taking an [online credit recovery] course effectively cancels out the negative association between having an IEP [individualized education program] and gaining course credit" (p. 51). Online credit recovery has remained a popular method to help students recover a failed credit, especially in larger schools, rural schools, or schools with lower graduation rates (Viano, 2021).

Not all studies have found that online credit recovery has had better outcomes than F2F (Atchison et al., 2023; Heinrich et al., 2019; Heppen et al., 2017; Rickles et al., 2023; Viano, 2023). Nourse (2019) found that SWD were less likely to pass an online credit recovery course. Nourse also found that students in Grades 9 and 10 passed online recovery at a slower rate than those in Grades 11 and 12 and that middle school standardized assessment data predicted success in online credit recovery. Rickles et al. (2023) found that students taking online credit recovery in English 9 in Los Angeles led to lower rates of recovering credit when compared to those in F2F recovery courses. Heppen et al. (2017) and Heinrich et al. (2019) both found that F2F classes provided better learning outcomes than online. Atchison et al. (2023) and Viano (2023) both found that neither online nor F2F produced learning outcomes at a significantly different level.

There have also been concerns about the academic rigor and learning outcomes of online credit recovery classes (Carr, 2014; Heinrich et al., 2019; Powell, Roberts, et al., 2015). Many online options—used by some districts as a cheaper alternative to F2F recovery—have "lowered the bar for passing" (Powell, Roberts, et al., 2015, p. 10), requiring "very little of students in

demonstrating proficiency" (p. 10; see also Viano & Henry, 2023). Similarly, there have also been concerns that online recovery courses are easier because answers to practice and assessment can be found online (Heinrich et al., 2019; Viano, 2021). Atchison et al. (2023) found that an online credit recovery program that had cheaper front-end costs did not account for all of the future costs of the program, and some F2F programs were ultimately cheaper when considering all costs.

Heinrich and Cheng (2022) found that graduates with a lower future earning potential were significantly more likely to have taken an online credit recovery course. This potential earning differential was found to start 4 years after high school graduation. Furthermore, students taking online credit recovery courses were significantly less likely to enroll in college; student enrollment in prestigious universities was even lower (Heinrich & Darling-Aduana, 2021).

There has also been limited research on the general effectiveness of online credit recovery in secondary schools (Rickles et al., 2018; Viano & Henry, 2023). Many studies of online learning have focused on postsecondary settings or online learning to accelerate student coursework (Heppen et al., 2017; Rickles et al., 2018). Three cases are presented below that focused on online credit recovery in U.S. public high schools. The first case consists of two multi-year studies set in Chicago Public Schools (CPS) comparing the effectiveness of online credit recovery and F2F credit recovery (Heppen et al., 2017; Rickles et al., 2018). The second case consists of multiple studies that focused on the implications of online courses in another large urban Midwestern public school district (Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021). Finally, the third case is a study that examined graduation and test score outcomes for students who took online credit recovery in North Carolina (Viano & Henry, 2023).

Case 1: Algebra 1 Recovery in Chicago

Bailey et al. (2017) found that "timely mastery of algebra in the early high school years may also provide crucial 'foot-in-the-door' advantages for keeping a student on track for a chance at a four-year college education" (p. 22). Furthermore, Grade 9 students, particularly students who were Black or Hispanic, were more likely to be retained and not promoted to the next grade than students of any other grade in high school (Warren et al., 2014). Within this context, Heppen et al. (2017) conducted an experimental study to determine how one online credit recovery program helped CPS students recover a credit in Algebra 1 compared to a F2F option. In the sample, 1224 students who were taking summer school to recover an Algebra 1 credit were selected across 17 CPS high schools in 2011 and 2012 (Heppen et al., 2017). On the first day of summer school, each student was randomly assigned the treatment, online credit recovery, or the control, F2F credit recovery (Heppen et al., 2017). To improve internal validity, students were blocked by their gender and by their success in the first semester of Algebra 1; each participating student also took a math pretest (Heppen et al., 2017).

The treatment group and control group were similar in multiple ways beyond gender and semester credit success (Heppen et al., 2017). Students in CPS take standardized tests in both Grades 9 and 10, and there was no statistically-significant difference between the control or treatment groups in how they performed on the math section of the Grade 9 assessment (Heppen et al., 2017). Consequently, the lack of a significant difference in standardized math test scores suggested that baseline student math skills of both groups were similar at the start of the experimental study (Heppen et al., 2017). Approximately 12% of each group was comprised of students who were SWD (Heppen et al., 2017).

Recovery Outcomes in Chicago. During the experimental study, all students accessed their recovery courses during the day at a physical school in CPS (Heppen et al., 2017). Students in F2F credit recovery classes were taught in-person by certified mathematics teachers in CPS who had an average of 14 years of teaching experience (Heppen et al., 2017). Students in the online credit recovery group were taught virtually by certified mathematics teachers with an average teaching experience of 5 years, hired by the online recovery provider, Aventa (Heppen et al., 2017). Students in the online credit recovery group were also supported in the classroom by a certified CPS teacher; approximately 53% of these mentor teachers were certified in mathematics (Heppen et al., 2017). Students completed the credit recovery course, and, at the conclusion of summer school, students took a math posttest and student experience survey (Heppen et al., 2017). In 2011, there were 18 sections of F2F recovery and 18 sections of online recovery; in 2012, there were 20 sections of each group (Heppen et al., 2017).

Students receiving F2F recovery performed significantly better on the posttest than students receiving online recovery—40% versus 38%, respectively; however, these scores "suggest that students in both conditions generally performed poorly on the posttest" (Heppen et al., 2017, p. 290). While a majority of students in both groups were successful in recovering their Algebra 1 credit, students in the F2F recovery were significantly more likely to recover the credit than students who were in online credit recovery (Heppen et al., 2017). Heppen et al. (2017) also considered whether students in the online recovery group who had an in-person mentor certified in math recovered credit at a higher rate than students in the online recovery group whose mentor teacher was certified in a different subject, but there was not a significant difference—68% of students with a math-certified mentor recovered credit compared to 65% for students with other-certified mentors.

These results contradicted findings in a survey of students who participated in credit recovery in Florida (Hart et al., 2019; Hughes et al., 2015). In contrast, Hart et al. (2019) and Hughes et al. (2015) found that students taking online recovery were more likely to earn course credit than those in the F2F setting. With this in mind, Florida studies were different in their composition from the Chicago study—Hart et al. and Hughes et al. studied multiple districts, courses, and online providers across Florida for 5 years, whereas Heppen et al. (2017) studied a single district, course, and online provider for 2 years. Hart et al. specifically referenced this contradiction in the discussion of the findings, indicating that the differences in findings between the two studies may have been related to the math-specific and economically-disadvantaged-population setting of the Heppen et al. study.

While posttest scores and recovery rates were higher for F2F students in the Heppen et al. (2017) study, there was no significant difference in scores between the groups when taking the next standardized math assessment. The average score for each subtest was higher for those in the online group than the F2F control group, albeit insignificantly (Heppen et al., 2017). These results more closely reflected the results found by Hart et al. (2019) and Hughes et al. (2015).

On the post-course experience survey, both groups reported similar levels of engagement and individualized support (Heppen et al., 2017). The group of F2F students reported their class was easier and clearer about what to do, while online students reported being more comfortable with computers (Heppen et al., 2017). Students from both groups also earned their next math credit at a similar rate (Heppen et al., 2017). Students in the F2F recovery group earned their next math credit at a rate of 54% for the 2011 group and 48% for the 2012 group; students in the online recovery group earned their next math credit at a rate of 53% in 2011 and 47% in 2012 (Heppen et al., 2017). While Heppen et al. (2017) focused on comparing the two delivery options

(online and F2F), there was not a discussion of how student characteristics, including but not limited to SWD, EL, students who are homeless, Black students, and Hispanic students, interacted with the delivery options because the randomized groups were intended to be as similar as possible.

Recovery and Graduation Rates in Chicago. Rickles et al. (2018) followed the same students through their first 4 years in high school in CPS. Rickles et al. (2018) were interested in evaluating the longer-term outcomes of credit recovery, both online and F2F. The study focused on how many math credits students earned in the first 4 years of high school as well as the rate with which these students graduated from high school (Rickles et al., 2018). Rickles et al. collected data on graduation and the number of math credits earned in addition to other student categorical information, including but not limited to student race, gender, neighborhood poverty, and school attendance. Of the original students in the previous study, 70% remained in CPS to be included in the Rickles et al. study, and the groups were deemed sufficiently similar to the sample from the Heppen et al. (2017) study to compare high school academic performance in math and on-time graduation rates.

Both groups, online and F2F, earned math credits at a similar rate following credit recovery (Rickles et al., 2018). However, students in both groups were, on average, between one and two credits behind in earning the math credits needed to graduate in CPS (Rickles et al., 2018). Additionally, both groups had an OTGR of approximately 47% (Rickles et al., 2018). As with the Heppen et al. (2017) study, these findings similarly contradicted findings from Stallings et al. (2016), Hart et al. (2019), and Hughes et al. (2015). Stallings et al., Hart et al., and Hughes et al. found that students participating in online credit recovery were significantly more likely to graduate on time than students who participated in F2F recovery classes. Correspondingly,

Stallings et al., Hart et al., and Hughes et al. had far broader populations and sampling frames (multiple districts, multiple courses, and multiple online providers) than did Rickles et al. (2018). According to Hart et al., these differences may have accounted for the contradictory findings.

With online recovery and F2F recovery having had similar academic performance and graduation rates, Rickles et al. (2018) then examined the OTGR of participants in either type of CPS Algebra 1 credit recovery—F2F or online—compared to the OTGR of nonparticipants. Rickles et al. considered five different classifications of CPS students based on their performance in Algebra 1 and credit recovery in their first year of high school: (a) passed Algebra 1 in Grade 9 with a C or better, (b) passed Algebra 1 in Grade 9 with a D, (c) failed Algebra 1 in Grade 9 but recovered the credit through credit recovery that summer, (d) failed Algebra 1 and failed credit recovery that summer, and (e) failed Algebra 1 and did not attempt credit recovery that summer. As shown in Table 1, these classifications were predictors of both the average of math credits earned and rate of graduation at the end of a student's fourth year (Rickles et al. 2018). Students earning below a C in Algebra 1, on average, earned fewer math credits than the six credits needed for graduation (Rickles et al., 2018). Students who passed Algebra 1 with a C or better earned an average of 6.6 math credits and had an OTGR of 89% (Rickles et al., 2018). Students who passed Algebra 1 with a D earned an average of 5.8 math credits and had an OTGR of 73% (Rickles et al., 2018). Students who failed Algebra 1 but recovered the credit earned an average of 4.8 math credits and had on OTGR of 51% (Rickles et al., 2018). Students who failed both Algebra 1 and the recovery earned an average of 3.2 math credits and had an OTGR of 27% (Rickles et al., 2018). Students who failed Algebra 1 and did not participate in the recovery earned an average of 3.1 math credits and had an OTGR of 27% (Rickles et al., 2018). Earning the Algebra 1 credit significantly improved a student's potential on-time graduation as

did passing the recovery if the students failed Algebra 1 (Rickles et al., 2018). These findings were similar to the findings from Bailey et al. (2017) that earning the Algebra 1 credit was an important step towards on-time graduation.

Table 1

Outcomes for Algebra 1 Grade and Recovery Participation Classification

Classification	Average Math Credits Earned [a]	OTGR
Passed Algebra 1 with a C or better	6.6	89%
Passed Algebra 1 with a D	5.8	73%
Failed Algebra 1, and passed credit recovery	4.8	51%
Failed Algebra 1, and failed credit recovery	3.2	27%
Failed Algebra 1, and did not participate in credit recovery	3.1	27%

Note. Adapted from "Online Credit Recovery and the Path to On-Time High School Graduation," by J. Rickles, J. Heppen, E. Allensworth, N. Sorenson, and K. Walters, 2018, *Educational Researcher, 47*(8), p. 488 (https://doi.org/10.3102/0013189x18788054).

[a] Six credits were required for graduation in CPS. One credit is given for a passing grade each semester.

As noted in Table 1, credit recovery as an intervention had positive outcomes for on-time graduation regardless of the mode of delivery (Rickles et al. 2018). Other indicators, such as passing Algebra 1, showed greater outcomes on OTGR compared to those who failed and participated in credit recovery (Rickles et al. 2018). To explain reasons behind the finding that credit recovery may not have been as strong an influencer on OTGR as other factors, Rickles et

al. (2018) concluded that “it may be unrealistic to expect a single credit recovery course, whether online or [F2F], to put failing students back on the path to on-time graduation” (p. 489). Since both modes of recovery resulted in similar OTGR outcomes, Rickles et al. also recommended that schools or school districts could use a cost-benefit analysis to see which mode of delivery is best when offering a credit recovery intervention – for example, an in-person recovery option may be cost prohibitive when compared to a cheaper online option or vice versa. Atchison et al. (2023) indicated that there are many costs to consider when considering online or F2F recovery, including teacher-incurred costs and staffing costs, depending on the model selected.

Case 2: Participation in and Impact of Online Courses in an Urban Midwestern District

In a large urban district in the Midwestern United States, Heinrich et al. (2019) studied online course enrollments and completion from 2013–2017. The district served around 21,000 high school students each year with approximately 25% of them accessing online courses in 46 high schools (Heinrich et al., 2019). Approximately 22% of the high school students in the district were SWD (Heinrich et al., 2019). Also, 8% of the high school students in the district were EL over the first 3 years of the study; this group of students doubled to 16% in the final year of the study (Heinrich et al., 2019).

Online Course Participation. Student participation in online courses varied from school to school (Heinrich et al., 2019). Heinrich et al. (2019) noted that many of the online course students were centered in certain schools, such as alternative schools or those in certain geographic locations in the district. The study reported,

> nearly all students using the online instructional program were in the same three (of eight) school zones that follow the district’s early calendar start time, and a number of the

> high school zip codes with relatively higher proportions of online course-takers are in inner-city, high poverty areas. (Heinrich et al., 2019, p. 2164)

Heinrich et al. also found that school-level administrators and leaders made decisions that impacted what programs were offered and how students were encouraged to participate in online courses. School leaders were also influenced by the recommendations of and practices set by district-level administrators and leaders (Heinrich et al., 2019) This, according to Heinrich et al., explained large variability in student participation in online courses from year to year. For example, one high school saw an increase of 33 percentage points in students taking online courses one school year, while another saw a decrease of 50 percentage points the next year (Heinrich et al., 2019). One high school had 23% of its students taking online courses in 2014, 59% in 2015, 9% in 2016, and finally 0% in 2017 (Heinrich et al., 2019).

Heinrich et al. (2019) also found that certain student factors predicted whether a student would enroll in an online course. For example, both SWD and EL were groups of students who, over the course of the study, were significantly less likely to take an online class (Heinrich et al., 2019). In contrast, students who failed a class or were in Grades 10-12 were significantly more likely to take an online course, thus "affirming the 'credit recovery' focus on online instruction in the district" (Heinrich et al., 2019, p. 2165). Students taking 4 years of online courses were also over seven times more likely to have failed a course (Heinrich et al., 2019). This focus of online courses being used for credit recovery purposes was similar to findings from studies across the United States (Frazelle, 2016; Hart et al., 2019; Viano, 2021).

For students enrolled in an online course, Heinrich et al. (2019) found that the grade level of the student was significantly associated with the student's grade point average and total number of earned credits. For students in Grades 11 and 12, students were likely to have higher

GPAs and total number of credits earned; however, for students in Grades 9 and 10, students were likely to have lower GPAs and total number of credits earned (Heinrich et al., 2019). Despite the positive implications of earned credits and grade point average increases for older students, test scores in reading and math for all grades, on average, were significantly lower than that of other high school students in the district (Heinrich et al., 2019). In response to this finding, Heinrich et al. (2019) stated "that, on average, online course taking is not benefiting students or reflecting real learning, and some students may even be set back in their learning" (p. 2174). These conclusions—positive academic implications coupled with other stagnant learning measures—were similar to the results found nationally by Sublett and Chang (2019), both Heppen et al. (2017) and Rickles et al. (2018) in Chicago, and Viano and Henry (2023) in North Carolina.

Multiple teachers involved in the district's online learning indicated that SWD often failed to get required accommodations or individualized support because of either the lack of accommodations within the program itself or the lack of student accommodation information being relayed from F2F teachers to the online teacher (Heinrich et al., 2019). Heinrich et al. (2019) also found passive engagement by students while participating in the online courses, with students opting to watch unrelated videos or search online for answers to assignments or assessments as opposed to actively engaging with the courses. Heinrich et al. questioned the desired goal of these students in online classes, asking whether the student's goal in online classes was to simply complete the course or to improve their learning and understanding of the content. Darling-Aduana et al. (2019) countered that students in these courses rarely get the consistent support from instructors needed by the students.

Heinrich et al. (2019) also questioned, with the observed lack of learning by students, whether the goal of online programs in this district was always improved academic outcomes. Instead, the researchers concluded that the goal of these online programs may have been to serve the varying, different, and unique needs of the students taking the courses (Heinrich et al., 2019). For example, online courses provided flexible spaces for students who need non-traditional settings or provided a nontraditional focus on life skills for students who would not have been successful with traditional learning (Heinrich et al., 2019). Some teachers described the difficult lives of some students and the non-academic supports that are provided with online courses, offering "a 'safe space' for students who might otherwise not be in school" (Heinrich et al., 2019, p. 2179). The impact of online classes may have had an impact beyond academics (Darling-Aduana, 2019; Heinrich et al., 2019; Pettyjohn & LaFrance, 2014). This finding supported the findings of Powell, Roberts, et al. (2015) who indicated that the most successful online credit recovery programs have a F2F component that allows the course to be tailored to the individual needs of the student.

Online Course Implications and Impact. Heinrich and Darling-Aduana (2021) continued to study this Midwestern urban district's online course program, expanding the scope of data from 2013–2017 to 2010–2018. This expansion increased the sample size to n = 47,113 students (Heinrich & Darling-Aduana, 2021). Of the high school students during this time period, 40% (n = 20,249) took at least one online class; the average online-course-taking students took two online classes during their high school career (Heinrich & Darling-Aduana, 2021). Heinrich and Darling-Aduana also continued to measure *online course intensity*—how often and how many online courses students were taking in the district. Students taking only one or two courses over a two-year stretch, categorized as the least intense category, made up n = 12,014

students in the sample (Heinrich & Darling-Aduana, 2021). Students taking three or more courses in a two-year stretch made up *n* = 5,414 students in the sample (Heinrich & Darling-Aduana, 2021). Finally, students taking multiple courses over 3 or 4 years, the most intense level, accounted for *n* = 2,662 students in the sample (Heinrich & Darling-Aduana, 2021). While *failing at least one course* remained the leading predictor of students who took an online course, the SWD category flipped to show a significant proportion of its students taking an online course as opposed to not taking one (Heinrich & Darling-Aduana, 2021). EL, however, remained significantly less likely to enroll in an online course (Heinrich & Darling-Aduana, 2021). These findings contradicted the finding of the likelihood of SWD enrolling in online courses from the Heinrich et al. (2019) study, but it confirmed the finding regarding EL (Heinrich & Darling-Aduana, 2021).

From 2010–2018, the rate at which students failed courses in the district generally decreased over time, and the OTGRs mirrored the failure rate by increasing at a similar rate (Heinrich & Darling-Aduana, 2021). Overall, students who did not take an online course graduated at a rate three percentage points higher than those who did take an online class (Heinrich & Darling-Aduana, 2021). However, of those student characteristics associated with likely taking an online course (e.g., failing a class), taking an online course in the district was associated with significantly higher graduation rates of approximately 10 percentage points when compared to those who did not take an online course (Heinrich & Darling-Aduana, 2021). Heinrich and Darling-Aduana (2021) explained that these connections "suggest that the opportunity to recover failed credits online may play an important role in students' progress toward high school completion" (p. 382). These findings were similar to those of Hart et al. (2019) who identified that students using online recovery courses were 10 percentage points

more likely to graduate on time when compared to students who used F2F recovery courses in Florida.

Despite the increase in likelihood of graduating high school, the postsecondary experiences for students were different for students who took online courses in high school compared to students who did not take online courses (Heinrich & Darling-Aduana, 2021). Students taking online courses were approximately 10 percentage points less likely to enroll in college, and they were 30 percentage points less likely to attend a university that awarded a degree beyond the undergraduate level (Heinrich & Darling-Aduana, 2021). Heinrich and Darling-Aduana (2021) also estimated that online credit recovery, as used in this district, saved the district 50% of the cost of having students repeat the class in a traditional classroom—an estimated savings of $1,112 per student. However, concerns persisted about the quality of the online learning with the lack of positive postsecondary outcomes (Heinrich & Darling-Aduana, 2021).

Case 3: Online Credit Recovery in North Carolina

Viano and Henry (2023) studied the relationship between credit recovery and outcome variables of earning credit, performance on tests, and high school graduation in North Carolina schools. In particular, Viano and Henry were interested to identify whether gaps existed in learning and on-time graduation among certain student groups, including but not limited to Black students, Hispanic students, economically-disadvantaged students, and SWD, depending on how the student took recovered the credit—online or F2F (Viano & Henry, 2023). The sample was comprised of all high school students in North Carolina who failed a required core-subject course in high school between 2013–2017 (Viano & Henry, 2023). Despite being a nonexperimental ex post facto study, Viano and Henry (2023) used weighting within the sample to replicate

randomness of assignment to treatment, online or F2F, so that causal inferences could have been found.

Viano and Henry (2023) used student-level data from a state database to create variables in the study. Outcome variables were recovering the failed credit, student score on the end-of-course assessment, and on-time graduation (Viano & Henry, 2023). Viano and Henry (2023) tracked whether students participated in online credit recovery (treatment), participated in F2F credit recovery (alternative treatment), or did not participate in recovery (control). School-level and student-level covariate variables were also considered, and they were measured prior to student enrollment in high school to control for any affect credit recovery enrollment might have had on outcome variables (Viano & Henry, 2023). School-level covariates included enrollment and percentages of certain student groups including EL, SWD, status as economically disadvantaged, and student race and ethnicity (Viano & Henry, 2023). Viano and Henry also considered student-level covariates of GPA, enrollment in advanced or remedial classes, whether the student failed a class in Grade 8, number of days absent in Grade 8, gender, status as EL, status as gifted, status as SWD, status as economically disadvantaged, approximate age in Grade 8, whether the student was overage in Grade 8, and student race and ethnicity. Finally, Viano and Henry recorded the year in which students failed their first high school class, the number of behavior referrals a student received in that year, and the difference between the student's failing assessment score and the score required to pass.

Viano and Henry (2023) found that students who participated in online credit recovery earned the credit at a significantly higher rate (58%) than students who participated in F2F recovery (39%). This held true for all subjects and student groups, and the gap was widest for economically-disadvantaged students in English and science and for Black students in science

and social studies (Viano & Henry, 2023). Test scores, however, were significantly lower for students in online credit recovery compared to students in F2F recovery (Viano & Henry, 2023). For the outcome of on-time graduation, all groups of students were more likely to graduate on time if they participated in online credit recovery compared to F2F recovery, and the gap was widest for Hispanic students and for students who are economically disadvantaged (Viano & Henry, 2023).

Viano and Henry (2023) found that online credit recovery led to higher rates of on-time graduation; however, they also found that it "appears to result in less student learning compared to F2F" (p. 29). Viano and Henry indicated that online credit recovery may have been an intervention that provided students of underrepresented groups a higher probability of graduating on time. These findings also suggested that online credit recovery courses did not have the same rigor or content as the F2F recovery courses because graduation rates increased without a corresponding increase in academic test scores (Viano & Henry, 2023). The setting and findings of this study (Viano & Henry, 2023) were similar to the setting and findings of Hart et al. (2019) and Stallings et al. (2016), and the studies all had similar findings of online credit recovery resulting in higher OTGRs than students who participated in F2F recovery.

Summary

High school graduation has had positive implications for individuals, schools, and society (Bailey et al., 2020; Qu et al., 2016; Vining & Weimer, 2019). Despite increasing graduation rates in the United States, some students have still struggled to graduate on time (Heinrich & Darling-Aduana, 2021; McFarland et al., 2020; Rickles et al., 2018; Uretsky, 2019). Furthermore, underrepresented groups of students have tended to graduate at a lower rate than that of their peers (Atwell et al., 2019; McFarland et al., 2020). Faced with federal accountability

measures, school leaders have been motivated to implement interventions to support at-risk students (Choi, 2011; Vasquez Heilig et al., 2012). Online credit recovery has become a popular intervention for schools and districts to support OTGR for at-risk student populations (Atchison et al., 2023; Powell, Roberts, et al., 2015; Viano, 2021), and researchers have been studying the long-term outcomes of these programs (Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021; Heppen et al., 2017; Rickles et al., 2018; Viano & Henry, 2023). Several studies focused on online credit recovery have been set in single school districts, limiting generalizability to other schools, other districts, and other online program providers (Heinrich et al., 2019; Heppen et al., 2017; Rickles et al., 2018). Findings from these studies contradicted findings that from studies that used state-wide data and found that participants of online credit recovery graduated at higher rates than those who participated in other settings such as F2F (Hart et al., 2019; Stallings et al., 2016; Viano & Henry, 2023). Further research examining student participation in online credit recovery and their subsequent on-time graduation could provide an important perspective in this growing field of research (Heinrich & Darling-Aduana, 2021; Rickles et al., 2018; Viano & Henry, 2023).

Chapter 3

Methodology

This chapter begins with a review of the purpose of the study and the corresponding research questions. It describes the paradigm and quantitative design of the study followed by an overview of the setting and sample, collection of data, and procedures for analyzing the data. Hypotheses and inference tests for each research question are then discussed. The last section of the chapter discusses the validity and reliability of the findings in the study.

Purpose of the Study

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate in online credit recovery—both those who were eligible for participation and those who were never eligible. Student factors considered in this study were gender, race and ethnicity, status as an English learner (EL), status as a student with a disability (SWD), status as economically disadvantaged, status as homeless, student's high school, and student's graduation cohort.

Research Questions

This study examined student participation in and graduation-rate outcomes of online credit recovery in a large school division in Virginia guided by the following research questions:

1. What are factors that explained student participation in online credit recovery?
2. How much more or less likely were students who participated in online credit recovery to graduate high school on time compared to (a) the likelihood of those

who were eligible for, but did not participate in, online credit recovery and (b) the likelihood of those who were never eligible for online credit recovery?

Paradigm

A postpositivist paradigm was used as the underlying guide for the methodology of this study. Creswell and Creswell (2018) defined postpositivism as a "deterministic philosophy" (p. 25) where certain "causes (probably) determine effects or outcomes" (p. 25), and researchers can reduce the problem into smaller set of variables that can be tested in order to refine theories of causes and outcomes. A postpositivist study seeks to explain an objective truth of what exists while also acknowledging that a perfect absolute truth cannot be determined (Creswell & Creswell, 2018).

Research Design

This study was quantitative, *ex post facto,* and non-experimental with the purpose to identify factors that explained participation in online credit recovery and to identify differences in the likelihood of on-time graduation given whether a student was eligible for and participated in online credit recovery. A quantitative approach was best since the study sought to identify "factors that influence an outcome" (Creswell & Creswell, 2018, p. 36) and understand "the best predictors of outcomes" (p. 36). Even if the question were causal in nature, non-experimental research does not manipulate independent variables because it is impossible, unethical, or not feasible; this research measures variables as they exist (Jhangiani et al., 2019). This study was also ex-post facto in nature as all data were gathered from historical student records kept by a school division (Salkind, 2010). Ex post facto designs are appropriate when circumstances have happened naturally, when it is impossible or impractical to manipulate the independent variables, or when such manipulation is unethical (Salkind, 2010).

This study used a correlational design to determine possible associations between the independent explanatory variables and the dependent variable for each research question (Salkind, 2010). Research Question 1 required a correlational approach to identify explanatory student factor variables, such as race or gender, that explained the dependent variable of participation in online credit recovery (Creswell & Creswell, 2018; Jhangiani et al., 2019). Research Question 2 used a correlational approach to compare the likelihood of on-time graduation (dependent variable) of three mutually-exclusive participation groups of students (independent variable)—those who were never eligible for online credit recovery, those who were eligible for but did not participate in online credit recovery, and those who participated in online credit recovery—given covariates of student factors (Creswell & Creswell, 2018). In this study, for both research questions, non-experimental correlational research was preferred over experimental research because (a) available independent and dependent variable data was historical and could not be manipulated, (b) it was impossible to manipulate independent variables such as a student's race and ethnicity or whether a student was eligible for participation in online credit recovery, (c) randomly assigning a treatment of online credit recovery to eligible students may have been considered unethical, and (d) the study sought to describe how schools and a division were naturally implementing recovery given ethical and educational opportunity concerns of that recovery (Jhangiani et al., 2019).

Population, Setting, and Sample

A large school division in Virginia was selected as the setting for this study. The setting was also restricted to graduation cohorts for 2019 and 2020 as they formed the most recent consecutive school years that were not significantly affected by school closures associated with COVID-19 that began in March 2020. Online credit recovery participation and graduation rates

studies to date have generally included large districts as a setting—studies included two large urban Midwestern districts (Heinrich & Darling-Aduana, 2021; Rickles et al., 2018), all large North Carolina districts (Viano, 2021, 2023; Viano & Henry, 2023), and all large Florida districts (Hart et al., 2019).

Online Credit Recovery and Large School Districts

Watson et al. (2014) identified that a majority of large school districts, defined as districts with more than 25,000 students, have been using some variation of online learning. Tyner and Munyan-Penney (2018) indicated that larger schools have also been more likely to have credit recovery programs than smaller schools—those with enrollments of 1250 students or fewer. Large school districts have generally supervised and managed more schools than smaller districts; consequently, the large districts have not always known exactly how online learning has been utilized in each individual school (Alvarez & Marsal, 2018; Heinrich et al., 2019; Heinrich & Darling-Aduana, 2021; Watson et al., 2014). Both Heinrich et al. (2019) and Heinrich and Darling-Aduana (2021) found that individual schools within the same large district had varying levels of participation in the district's online program, a difference attributed to school leadership and district policy.

Large School Divisions in Virginia

There were 12 large school divisions in Virginia, serving over 724,000 students in 2019 and 2020; this was more than the enrollments of all remaining 120 medium and small school divisions combined (Virginia Department of Education [VDOE], n.d.-d). According to demographic regions assigned by the Weldon Cooper Center for Public Service at the University of Virginia (UVA, 2017), five of the large divisions were located in the Northern Region, four of the large divisions were located in the Hampton Roads Region, and three of the large divisions

were located in the Central Region. In 2019 and 2020, no large school divisions were located in the remaining regions of Eastern, Southside, Southwest, Valley, or West Central (UVA, 2017). More information about enrollment sizes in 2019 and 2020 for large school divisions is available in Appendix C.

Study Sample

Purposive sampling is a nonprobability sampling where participants are selected based on criteria set by the researcher and the purpose of the study (Etikan et al., 2016). Etikan et al. (2016) identified that nonprobability sampling is useful for a large population where randomization is impossible or impractical. Three large suburban school divisions—School Divisions A, B, and C—were selected to form the sampling frame based on criteria of (a) being a large school division with at least 25,000 students in 2019 and 2020 (Watson et al., 2014), (b) having an established online credit recovery program for at least 10 years measured from 2019 (Jones, 2011; Wyatt, 2017), and (c) forming a sample that included multiple geographic regions in Virginia (UVA, 2017). All three divisions had approximately 10 comprehensive public high schools with a total student enrollment of over 50,000 students in 2019. Each division was also among the 100 largest school districts in the United States in 2019 according to the National Center for Education Statistics (2021a). School Division C declined to participate in the study, and School Division B agreed to participate but encountered an unexpected issue with retrieving historical student data. School Division A agreed to participate and sent collected data.

The sample consisted of all students in the graduation cohorts of 2019 and 2020 from School Division A. As shown in Table 2, the VDOE (n.d.-b) provided data on the size and demographics of graduation cohorts for both 2019 and 2020. Rounded to the nearest thousand, School Division A had 5,000 students in each graduation cohort (VDOE, n.d.-b). Approximately

48% of students were female and 52% of students were male. White students were the largest race and ethnicity at approximately 49%, followed by Black students (27%), Hispanic (15%), and Asian (4%). Approximately 37% of students were economically disadvantaged, 2% were homeless, 7% were EL, and 12% were SWD. Table 2 provides more accurate percentages broken down by graduation cohort.

Table 2

Graduation Cohorts 2019 and 2020 in School Division A

Student Factors	Cohort 2019 %	Cohort 2020 %
Gender		
Female	47.1	48.3
Male	52.9	51.7
Race and Ethnicity		
Asian	3.2	3.8
Black	27.6	26.9
Hispanic	14.9	16.1
White	49.7	48.9
Economically Disadvantaged	36.2	37.9
Homeless	1.8	1.3
EL	6.0	6.9
SWD	11.2	11.8

Note. Percentage of the graduation cohort of the particular year is given to the nearest tenth for each student factor. Data were gathered from the VDOE (n.d.-b).

Using Virginia's measure for on-time graduation rate (OTGR), the Graduation and Completion Index (VDOE, n.d.-e), School Division A had an OTGR of over 90% in 2019 and showed an increase in 2020 as shown in Table 3 (VDOE, n.d.-b). Graduation rates were lower than average for students who were male (89%), Hispanic (77%), homeless (76%), SWD (85%), or EL (61%; VDOE, n.d.-b). Furthermore, students who were female (94%), Asian (97%), or White (94%) graduated at a rate higher than average (VDOE, n.d.-b). Table 3 displays on-time graduation rates for School Division A as well as the rates for certain student factors.

Table 3

OTGR for Graduation Cohorts 2019 and 2020 in School Division A

Student Factor	Cohort 2019	Cohort 2020
All students	90.7	92.0
Gender		
Female	93.0	94.2
Male	88.6	89.9
Race/Ethnicity		
Asian	96.3	98.4
Black	91.2	93.4
Hispanic	76.7	78.5
White	93.8	95.0
Economically Disadvantaged	86.5	88.0
Homeless	74.4	78.1
EL	60.6	62.8
SWD	83.1	88.2

Note. Data were gathered from the VDOE (n.d.-b) online *Graduation Cohort Build-a-Table*.

Data Collection

Prior to designing the study, the researcher completed the Social and Behavioral Research training through the Collaborative Institutional Training Initiative (see Appendix D). The Virginia Tech Institutional Review Board (VT IRB) reviewed the study, and they determined that the study was exempt from IRB review under Category 45 CFR 46.104(d) 4(ii) (see Appendix E). Proposals with a data request were sent to three school divisions which met the sampling criteria. Two school divisions – School Divisions A and B – agreed to participate, and School Division A sent data. School Division C declined to participate, and School Division B encountered an unexpected issue with retrieving historical student data.

Data Request

Historical data for students in Graduation Cohorts 2019 and 2020 and School Division A were collected and stored in a manner consistent with VT IRB protocols. The following data were collected:

- De-Identified Student Identifier. This was a unique code that allows the particular student to be cross-referenced across course grades and graduation data provided by the division.
- List of all online credit courses available from School Year 2015-2016 to School Year 2019-2020 (i.e., those online courses available to students in Graduation Cohorts 2019 and 2020).
- Transcript Data. List of all courses taken by, and grades earned by, students in Graduation Cohorts 2019 and 2020 to include the course's School Courses for the Exchange of Data (SCED) code (National Forum on Education Statistics, 2023).

- VDOE Exit/Withdraw Code. From the four-year cohort report, the exit/withdraw code (e.g., W731 or W880; VDOE, n.d.-g) and the corresponding school (see Appendix A for a list of all VDOE exit/withdraw codes).
- Student Factors. Student demographic information of gender, race and ethnicity, status as EL, status as SWD, and status as homeless. School Division A did not provide information about student status as economically disadvantaged.

Data Cleaning and Curation of Variables

Data are more than arbitrary numbers and values—decisions must be made on the appropriate way to represent the features, what should be highlighted, and how they should be coded in order to make it computable (Koltay, 2021). Data were cleaned using qualitative rules-based techniques (Ilyas & Chu, 2019). Additional variables, such as student grade point average (GPA) and participation in online credit recovery, were calculated based on collected data. Calculated categorical variables were coded with integers (see Appendix F; Kleinbaum & Klein, 2010). Collected categorical variables also received an integer code to represent particular categories in preparation for logistic regression (see Appendix F; Kleinbaum & Klein, 2010). This section describes how the collected data were used to create variables for data analysis and inference tests.

Data Cleaning. Data were inspected for incorrect or missing data qualitative rules-based techniques (Ilyas & Chu, 2019). Course codes were checked for typos and missing SCED codes. Student grades were inspected to ensure that each value was a letter. Student VDOE exit/withdraw codes were inspected to identify students who should be removed from the sample, included as an on-time graduate, or included as a not on-time graduate (see Appendix A).

Exit/withdraw codes were set by the VDOE to be consistent across all school divisions in Virginia (VDOE, n.d.-c; VDOE, n.d.-g). For example, the VDOE (n.d.-g) used Code W730 to indicate that a student received a high school diploma; students with this exit/withdraw code were coded as *on-time graduate* (1). Conversely, the VDOE (n.d.-g) used Code W880 to indicate that a student dropped out of school; students with this exit/withdraw code were coded as *non-graduate* (0). The VDOE (n.d.-g) used Codes W402 and W503 to indicate that a student transferred to another school; students with this exit/withdraw code were excluded from the study. See Appendix A for a list and description of all VDOE (n.d.-g) exit/withdraw codes and how each was treated in the study.

Variable Computation and Coding. Additional variables—student GPA, eligibility for online credit recovery, participation in online credit recovery, and participation group—were calculated based on collected data. Student grades were used to calculate an unweighted GPA where 4 points were assigned for a grade of "A" or "A+," 3 points were assigned for a grade of "B+" or "B," 2 points were assigned for a grade of "C+" or "C," 1 point was assigned for a grade of "D+" or "D," and 0 points were assigned for a grade of "F" or "WF" (Lang, 2007). No points were assigned for grades of "I," "N," "NC," "P," "W," and "WP." The variable GPA was calculated by multiplying the number of credits for the course by the student's GPA for that course, adding all such numbers for the student, and dividing that by the sum of credits taken; the result was a number between 0.00 and 4.00 inclusive, rounded to two decimal places (Lang, 2007).

Values of GPA were inspected for qualitative rules-based cleaning and missing values. Values were surveyed to ensure that no value was greater than 4.00 or less than 0.00. Missing GPA values were classified as missing completely at random, missing at random, or missing not

at random; reasons for the missing values were considered to avoid any biased listwise deletion (Newman, 2014). Students in the graduation cohort who never took a course with the division were removed from the sample, and students without a GPA and selected to remain in the sample were assigned a GPA of 0.00.

School Division A identified courses that were delivered online; any course with the same SCED code as an online course was coded as *connected to an online course*. Students who failed a course connected with an online course were identified as *eligible* for online credit recovery (1), and students who never failed a connected course were identified as *not eligible* (0). Students who were eligible and who then took a connected online course were identified as *participated in online credit recovery* (1); students who did not take such an online course, or those who did not fail an eligible course, were identified as *not participated* (0). Each student was also coded into one of three participation groups – students who were never eligible for online credit recovery (0), students who were eligible for but did not participate in online credit recovery (1), and students who participated in online credit recovery (2).

Categorical Variable Coding. Categorical variables were assigned values based on the category in anticipation of binary logistic regression (Howell, 2013). Dichotomous categorical variables received a code of 0 or 1. Polytomous categorical variables received a code of 0 through $n - 1$, and one of the categories was selected as the reference category (Cohen et al., 2003; Hardy, 1993; Orme & Combs-Orme, 2009).

***Dichotomous Categorical Variables*.** Dichotomous categorical variables are variables that have only two different values or categories (Howell, 2013). Student status as EL was coded as *not EL* (0) or *EL* (1). Student status as SWD was coded as *not SWD* (0) or *SWD* (1). Student status as economically disadvantaged was coded as *not economically disadvantaged* (0) or

economically disadvantaged (1). Student status as homeless, identified through the proxy of a student who received services under the McKinney-Vento Act, was coded as *not homeless* (0) or *homeless* (1).

Polytomous Categorical Variables. Polytomous categorical variables are variables that have more than two different values or categories (Howell, 2013). For logistic regression, polytomous variables require $n - 1$ dummy variables, where n is the number of categories (Cohen et al., 2003; Orme & Combs-Orme, 2009). Variables of gender, race and ethnicity, school, and participation in online credit recovery were polytomous and required dummy variables. Student gender had three categories, and it required $3 - 1 = 2$ dummy variables (Cohen et al., 2003). Similarly, race and ethnicity had eight categories and required seven dummy variables, student school required 10 dummy variables, and participation group required 2 dummy variables.

For logistic regression analysis, one category within the polytomous variable must be selected to serve as a reference category (Cohen et al., 2003; Hardy, 1993; Orme & Combs-Orme, 2009). While this choice is arbitrary, Hardy (1993) provided a framework for selecting the reference category. For variables like gender and race and ethnicity, reference groups should be both well-defined and have one of the larger number of observations (Hardy, 1993). The categories of *female,* for the variable gender, and *White,* for the variable race and ethnicity (see also Viano, 2021), were selected as the reference category as each (a) was a sizable proportion of the sample (VDOE, n.d.-b) and (b) was identified by McFarland et. al (2020) and the VDOE (n.d.-b) as generally having had a higher-than-average OTGR. For *school,* the school with the highest proportion of its students participating in online credit recovery was selected as the reference category. Participating in online credit recovery served as the reference category for

the participation group variable. Table 4 shows examples of coding for *gender* variables X_1 and X_2 where female is the reference variable. Table 5 shows examples of coding for *race and ethnicity* variables X_3 through X_9 where White is the reference variable. Dummy variable coding for all other polytomous categorical variables followed a similar procedure.

Table 4

Dummy Variable Coding for Gender

Gender	Student Gender Variables	
	X_1	X_2
Female	0	0
Male	1	0
Other	0	1

Note. The category *female* has been selected as the reference category.

Table 5

Dummy Variable Coding for Race and Ethnicity

Race and Ethnicity	Variable Codes						
	X_3	X_4	X_5	X_6	X_7	X_8	X_9
American Indian or Alaska Native	1	0	0	0	0	0	0
Asian	0	1	0	0	0	0	0
Black or African American	0	0	1	0	0	0	0
Hispanic	0	0	0	1	0	0	0

Race and Ethnicity	Variable Codes						
	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Native Hawaiian or Other Pacific Islander	0	0	0	0	1	0	0
Two or more races	0	0	0	0	0	1	0
Unknown	0	0	0	0	0	0	1
White	0	0	0	0	0	0	0

Note. The category *White* was selected as the reference category (Viano, 2021).

Data Analysis

Variables in this study were independent. The dependent variables were categorical and dichotomous, and the independent variables or covariates were nominal/categorical or quantitative/continuous (Howell, 2013); therefore, binary logistic regression was appropriate for regression analysis and inference testing (Kleinbaum & Klein, 2010; Orme & Combs-Orme, 2009). Binary logistic regression uses independent explanatory variables to determine if any are significantly associated with the dichotomous dependent variable (Opić, 2020). Logistic regression is of the form:

$$\text{logit } P(\mathbf{X}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \beta_0 + \sum \beta_i X_i \quad (1)$$

where X_n is an independent explanatory variable, β_n is the coefficient of the explanatory variable X_n, β_0 is the intercept of the regression, and $P(\mathbf{X})$ is the dependent variable that indicates a student's probability of being true—either a student who was expected to have participated in

online credit recovery (RQ 1) or a student who was expected to have graduated on time (RQ 2). SPSS generated models based on the framework developed by Hosmer et al. (2013).

Building the Logistic Regression Model

Hosmer et al. (2013) provided an iterative process for creating a logistic regression model. An *initial model* was created, and explanatory variables were purposefully selected for inclusion in the model as opposed to a stepwise selection (Bursac et al., 2008; Hosmer et al., 2013). Cross-tabulation tables were generated to identify outliers and empty cells (Hosmer et al., 2013; Orme & Combs-Orme, 2009). If there were cells that were empty across an entire variable, or if there were fewer than $n = 16$ students in a category, that variable was considered for elimination or consolidation prior to computation (Orme & Combs-Orme, 2009). For a continuous explanatory variable, a logistic regression model with that variable and the dependent variable was created to estimate the possible significance of the variable (Hosmer et al., 2013). Values for each student and variable were exported to SPSS.

The initial model was then created by SPSS, and variables were inspected for significance at the $\alpha = .05$ level (Hosmer et al., 2013). Variables that were not significant were considered for removal from the model, and another model was generated with the remaining variables (Hosmer et al., 2013). The coefficients of the new model were inspected to see if any changed by more than 20%; if any variable had such a change, the removed variables were considered for inclusion because it was deemed important to the model (Hosmer et al., 2013). This iterative process of removing and including variables was continued until no further changes were available (Hosmer et al., 2013).

If any variables were not selected for inclusion in the initial model, they were added individually to the model, and the process of identifying significant coefficients and removing

not significant variable was conducted again (Hosmer et al., 2013). After all variables had been considered, the resulting model was called the *main effects model* (Hosmer et al., 2013). The model was checked for interactions among its variables by creating a new model with one interaction variable; models were created for all variables included in the main effects model (Hosmer et al., 2013). Interaction variables that were significant were added to the main effects model, and additional models consisting of combinations of the interaction variables and the main effects model were considered (Hosmer et al., 2013). The resulting model was called the *preliminary final model* (Hosmer et al., 2013).

The final step in creating a logistic regression model was to check the fit and adequacy of the preliminary final model to ensure that it was an improvement over an intercept-only model (Hosmer et al., 2013; Peng et al., 2002). The Omnibus Tests of Model Coefficients was assessed for significance $p < .05$ (Orme & Combs-Orme, 2009; Smith & McKenna, 2013). The Hosmer-Lemeshow goodness-of-fit test was assessed for non-significance $p > .05$ (Hosmer et al., 2013; Peng et al., 2002; Smith & McKenna, 2013). Because the Hosmer and Lemeshow Test statistic tends to overestimate the true value, a second test was conducted by calculating the absolute differences between the expected ($\hat{e}$) and observed ($\hat{o}$) values, $|\hat{e} - \hat{o}|$,within each decile of the Hosmer and Lemeshow Test (Hosmer et al., 2013). For the decile with the largest absolute difference, the standardized difference was calculated (Hosmer et al., 2013):

$$\frac{|\hat{e} - \hat{o}|}{\sqrt{\hat{e}}}. \tag{2}$$

Hosmer et al. (2013) recommended that this standardized difference be at least 2.0 to trust that the results of the Hosmer and Lemeshow Test were close to the actual value and reliable.

A classification table was also created to determine how well the regression model would have actually predicted the participation of the students in the actual sample. The table was also

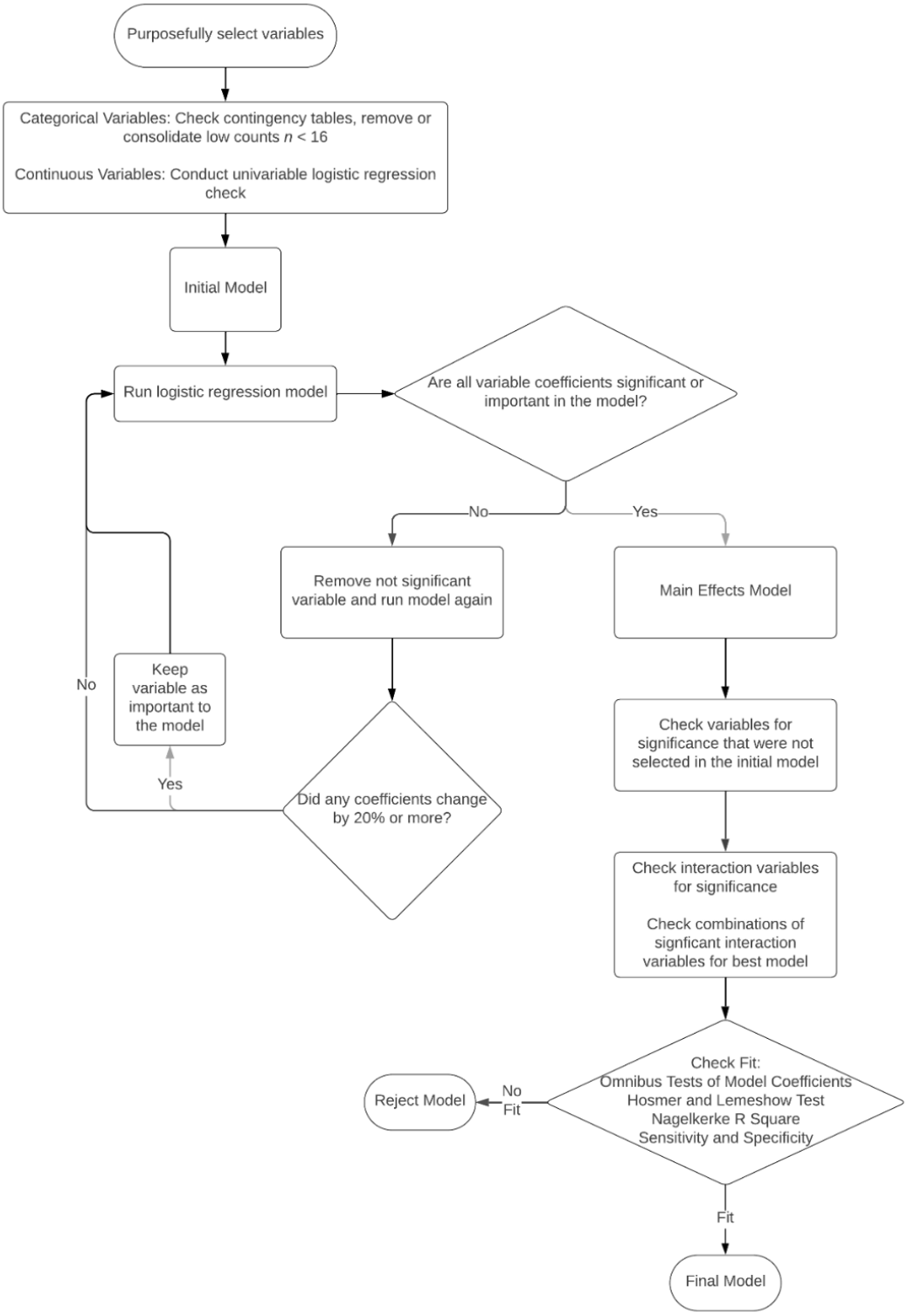
used to calculate the specificity and sensitivity of the model (Hosmer et al., 2013; Swift et al., 2019). Sensitivity is calculated as the number of true positives divided by the sum of the number of true positives and the number of false positives (Swift et al., 2019). Specificity is calculated as the number of true negatives divided by the sum of the number of true negatives and the number of false negatives (Swift et al., 2019). Models with low sensitivity are problematic as they are less likely to correctly identify the desired outcome (Swift et al., 2019).

The Nagelkerke R Square was also reported, called a *pseudo-R^2 value* because of its similarity to the R^2 value calculated in linear regression (Opić, 2020). An R^2 value shows that data fit the model better when the value is closer to one than to zero (Opić, 2020). Glynn (2010) recommended that the Nagelkerke R Square value be at least .30 for predictive purposes.

Given consideration of the fit and adequacy, the preliminary final model was either accepted or rejected as the final model. The final model was designed for use in inference testing for each research question. The flowchart of creating a final model using the Hosmer et al. (2013) framework is shown in Figure 2.

Figure 2

Flowchart of Creating a Final Logistic Regression Model



Research Question 1

Research Question 1 examined student factors that may have explained student participation in online credit recovery. Using the explanatory variables listed above and the binary dependent variable of participation, a logistic regression model was created to determine if any explanatory variables were significantly associated with the dependent variable (Opić, 2020). Explanatory variables considered for inclusion in the initial model were race and ethnicity, gender, school, GPA, status as SWD, status as EL, status as homeless, and status as economically disadvantaged (Bursac et al., 2008; Hosmer et al., 2013). A model was built using the Hosmer et al. (2013) framework.

The null and alternative hypotheses for Research Question 1 were:

- H_0: $\beta_1 = \beta_2 = \beta_n = 0$. No independent variable was associated with participation in online credit recovery; no variable coefficient was statistically significant in the model.
- H_A: Some $\beta_i \neq 0$. At least one independent variable explained participation in online credit recovery, because at least one variable coefficient was statistically significant in the model.

A Wald chi-square test was used at the $\alpha = 0.05$ level to determine statistical significance of the coefficients (Kleinbaum & Klein, 2010; Orme & Combs-Orme, 2009; Opić, 2020). For polytomous variables where dummy variables were utilized, such as race and ethnicity, a conclusion of significance for any specific category first required that the entire category have been shown to be significant (Orme & Combs-Orme, 2009). Independent explanatory variables with statistically-significant coefficients were considered to be associated with and explaining participation in online credit recovery.

Research Question 2

Research Question 2 considered an independent variable, *participation group*, that was composed of three mutually-exclusive groups of students: those who were never eligible for online credit recovery, those who were eligible but did not participate, and those who participated in online credit recovery. Participation in online credit recovery was selected as the reference variable so that the odds ratio of graduating on time for those who participated could have been compared to the other groups (Hardy, 1993; see Appendix F). Explanatory variables considered for inclusion in the initial model were race and ethnicity, gender, school, GPA, status as SWD, status as EL, status as homeless, and status as economically disadvantaged (Bursac et al., 2008; Hosmer et al., 2013). A model was built using the Hosmer et al. (2013) framework.

The initial null and alternative hypotheses for Research Question 2 were:

- H_0: $\beta_{\text{Group Participation}} = 0$. The coefficient for the independent variable of group participation was not statistically significant in the model.
- H_A: $\beta_{\text{Group Participation}} \neq 0$. The coefficient for the independent variable of group participation was statistically significant in the model.

A Wald chi-square test was used at the $\alpha = 0.05$ level to determine statistical significance of the coefficient (Kleinbaum & Klein, 2010; Orme & Combs-Orme, 2009). An initial set of hypotheses was necessary because, as a polytomous independent variable, logistic regression requires that the general categorical variable be significant before any conclusions of significant be drawn about the significance of its individual categories. If the initial null hypothesis were rejected, a second set of null/alternative hypotheses, separated for the two different cases, would have been considered.

Case 1: Not eligible. The category of *students who participated* was identified as the reference group; therefore, the coefficient for the category *not eligible for online credit recovery* (NotEligible), $\beta_{NotEligible,}$ would have been reported as compared to $\beta_{Participated}$. This created the following null/alternative hypotheses:

- H_0: $\beta_{NotEligible} = \beta_{Participated}$. There was no statistically-significant difference between the coefficient for those who were not eligible for online credit recovery and those who participated in online credit recovery.
- H_A: $\beta_{NotEligible} \neq \beta_{Participated}$. There was a statistically-significant difference between the coefficient for those who were not eligible for online credit recovery and those who participated in online credit recovery.

A Wald chi-square test would have been used at the $\alpha = 0.05$ level to determine statistical significance (Kleinbaum & Klein, 2010; Orme & Combs-Orme, 2009). A statistically-significant finding would have indicated that these two groups of students graduated on time at a different rate. Furthermore, given such a finding, the odds ratio (OR), calculated by $OR = \exp(\beta_{NotEligible})$, would have been reported to indicate how more or less likely the groups were to graduate on time.

Case 2: Eligible, but Did Not Participate. The category of *students who participated* was identified as the reference group; therefore, the coefficient for the category *eligible for but did not participate in online credit recovery* (EligibleDNP), $\beta_{EligibleDNP}$, would have been reported compared to $\beta_{Participated}$. This created the following null/alternative hypotheses:

- H_0: $\beta_{EligibleDNP} = \beta_{Participated}$. There was no statistically-significant difference between the coefficient for those who were eligible for but did not participate in online credit recovery and those who participated in online credit recovery.

- H_A: $\beta_{EligibleDNP} \neq \beta_{Participated}$. There was a statistically-significant difference between the coefficient for those who were eligible for but did not participate in online credit recovery and those who participated in online credit recovery.

A Wald chi-square test would have been used at the $\alpha = 0.05$ level to determine statistical significance (Kleinbaum & Klein, 2010; Orme & Combs-Orme, 2009). A statistically-significant finding would have indicated that these two groups of students graduated on time at a different rate. Furthermore, given a significant finding, the OR, calculated by $OR = \exp(\beta_{EligibleDNP})$, would have been reported to indicate how more or less likely the groups were to graduate on time.

Validity and Reliability

Internal validity refers to the "confidence that the specified causal agent is responsible for the observed effect on the dependent variable(s)," and external validity refers to the extent that causality may be applied to other groups of people, different settings, or different times (Anderson Dannels, 2019, p. 402). While there may have existed a causal relationship between one or more independent variables and one of the dependent variables in the study, a non-experimental correlational study does not seek to show causality (Jhangiani et al., 2019). Anderson Dannels (2019) indicated that non-experimental studies do not have an inherent need to discuss validity if they do not make causal inferences; however, "the validity of conclusions reached still requires evaluation" (p. 413). Furthermore, Anderson Dannels suggested that nonexperimental studies should rather consider *construct validity*—the question of whether the design and the statistics are appropriate to conclude that the independent and dependent variables covary. To this concern, discussion of the appropriateness for the sample, design, and statistical analysis were provided in this chapter.

Threats to potential internal and external validity existed. In discussing potential threats to internal validity, Rickles et al. (2018) identified that it is unreasonable to believe that a single intervention like online credit recovery could have eliminated all barriers to on-time graduation, particularly because a student who was eligible for participation may have had a number of factors that made the student at risk for graduating late or dropping out of school (see also Heinrich & Darling-Aduana, 2021). Additionally, both Rickles et al. and Heinrich and Darling-Aduana (2021) concluded that online credit recovery courses may or may not have provided an intervention that is better than other interventions available, such as face-to-face credit recovery. Furthermore, Heinrich and Darling-Aduana (2021) and Heinrich and Cheng (2022) identified that students who graduated having participated in online credit recovery did not have the same postsecondary outcomes as those who never took such courses (see also Viano & Henry, 2023). This indicated that the positive outcomes of graduation may not apply to all graduates (Heinrich & Cheng, 2022; Heinrich & Darling-Aduana, 2021).

Concerning external validity, the study did not use probability sampling in a way that would have allowed for a causal conclusion outside of the setting of the school division and time frame (Anderson Dannels, 2018). Similarly, when discussing the external validity of their findings, both Heinrich and Darling Aduana (2021) and Viano and Henry (2023) cautioned about projecting relationships between online credit recovery and graduation to other populations. Finally, this study was limited to the online recovery providers of the division as well as the decisions of the schools and division about what courses to have offered (Heinrich et al., 2019)—it was not possible to generalize the findings of this study to a district who may have used a different provider, made different decisions about what online courses to offer, or made

different decisions about how to emphasize, enroll, and support eligible students in online courses (Heppen & Darling-Aduana, 2021).

Reliability, defined as the accuracy and consistency of the collected data by Creswell & Creswell (2018), was also a concern as data was collected across 11 schools in the division. School divisions in Virginia have been required to develop plans for collecting, maintaining, and reporting data in a uniform way (VDOE, n.d.-c). The VDOE (n.d.-c) has collected data from local school divisions in a way that ensures "the usefulness, timeliness, accuracy, and comparability of education data" (Data Collection section, para. 6). Therefore, it was reasonable to assume that student historical data was reliable for school-to-school and division-to-division comparisons (VDOE, n.d.-c). Online credit recovery courses, however, have been provided by different providers depending on the school division (see Appendix B). This added an additional threat to reliability and generalizability of findings.

Summary

This chapter provided an overview of the methodology for this quantitative ex-post facto correlative study to identify associations between explanatory variables of student factors and dependent variables of participation in online credit recovery and rates of graduating on time. Purposive sampling was used to identify three large school divisions from multiple regions in Virginia based on set criteria to serve as the sampling frame; Graduation Cohorts 2019 and 2020 from the participating division were selected as the sample. Data collection and curation procedures were discussed to prepare the data for analysis and inference testing. Logistic regression was used to create a model designed to test hypotheses at the $\alpha = 0.05$ level for both research questions. The last section discussed the validity and reliability of the data, methods, and results.

Chapter 4

Presentation and Analysis of Data

This chapter provides a review of the purpose of the study and the two research questions on participation in online credit recovery and on-time graduation. Procedures for data cleaning and curation are described, and the sample is examined around student factors that were considered for use in logistic models. The process of building binary logistic regression models for each research question is explained, and the fit of the models to the collected data is discussed. Finally, a summary of the data and analysis is presented.

Purpose of the Study and Research Questions

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate in online credit recovery—both those who were eligible for participation and those who were never eligible. Student factors considered in this study were gender, race and ethnicity, status as an English learner (EL), status as a student with a disability (SWD), status as economically disadvantaged, status as homeless, student's high school, and student's graduation cohort.

Guided by the following research questions, this study examined student participation in and graduation-rate outcomes of online credit recovery in a large school division in Virginia:

1. What were factors that explained student participation in online credit recovery?
2. How much more or less likely were students who participated in online credit recovery to graduate high school on time compared to (a) the likelihood of those

who were eligible for, but did not participate in, online credit recovery and (b) the likelihood of those who were never eligible for online credit recovery?

Data Collection and Curation

Prior to designing the study, the researcher completed the Social and Behavioral Research training through the Collaborative Institutional Training Initiative (see Appendix D). The Virginia Tech Institutional Review Board (VT IRB) reviewed the study, and they determined that the study was exempt from VT IRB review under Category 45 CFR 46.104(d) 4(ii) (see Appendix E). Proposals with a data request were sent to the three school divisions—School Divisions A, B, and C—that met the sampling criteria. School Divisions A and B agreed to participate, and School Division C declined to participate. School Division A sent data for inclusion in this study; School Division B encountered an issue with retrieving historical student data and did not provide data for this study.

Data Collection

School Division A provided data on student characteristics of those who were in the Graduation Cohorts 2019 and 2020. Information collected included the student's school, race and ethnicity, gender, status as SWD, status as EL, status as homeless, and status as an on-time graduate or 4-year Virginia Department of Education (VDOE) exit/withdraw code. School Division A also provided a list of courses taken, corresponding School Courses for the Exchange of Data (SCED) code for the courses (National Forum on Education Statistics, 2023), and courses taken and grades earned by members of the cohorts. Finally, School Division A provided a list of online courses. School Division A did not provide any data about student status as economically disadvantaged. Data were stored in a manner consistent with VT IRB protocols and the data use agreement with School Division A.

Data Curation

Decisions were made on the appropriate way to represent the features, what should have been highlighted, and how they should have been coded in order to make them computable (Koltay, 2021). Qualitative data cleaning techniques were used to identify and correct errors, and they were also used to address typos, transposed characters, and missing values (Ilyas & Chu, 2019). Values from the collected data were then used to calculate additional variables of GPA, eligibility for participation in online credit recovery, participation in online credit recovery, and participation group.

Data Cleaning. Data were first inspected for incorrect or missing data using qualitative rules-based techniques (Ilyas & Chu, 2019). Of the 1773 unique course codes in the data, six course codes did not follow the course code convention of School Division A. The course code convention was a code of six characters—a mix of letters and numbers that began with and ended with a letter. Each instance of an incorrect course code was adjusted to be aligned with the convention. Courses that were corresponding, i.e., those with the same content or standards, were connected by SCED codes because corresponding courses had varying course codes and course titles. No missing SCED codes were found among the collected data. Student grades were inspected, and two grades were identified as numbers instead of letters; the grade of "70" was edited to be a "C," and the grade of "80" was edited to be a "B."

In School Division A, 10,892 students were included in Graduation Cohorts 2019 and 2020. Of those students, 828 were removed from the sample based on their VDOE exit/withdraw code (see Appendix A). Prior to calculating additional variables based on this collected data, and prior to qualitative rules-based data cleaning for calculated variables, 10,064 students were included in the sample.

Variable Calculations. Additional variables—student GPA, eligibility for online credit recovery, participation in online credit recovery, and participation group—were calculated based on collected and cleaned data. Student grades were used to calculate an unweighted GPA where 4 points were assigned for a grade of "A" or "A+," 3 points were assigned for a grade of "B+" or "B," 2 points were assigned for a grade of "C+" or "C," 1 point was assigned for a grade of "D+" or "D," and 0 points were assigned for a grade of "F" or "WF" (Lang, 2007). No points were assigned for grades of "I," "N," "NC," "P," "W," and "WP." The variable GPA was calculated by multiplying the number of credits for the course by the student's GPA for that course, adding all such numbers for the student, and dividing that by the sum of credits taken (Lang, 2007). The result, rounded to two decimal places, was a number between 0.00 and 4.00, inclusive.

The values of GPA were inspected for qualitative rules-based cleaning, and 169 students had a missing value for GPA. The missing GPA values were due to factors not collected by the data provided by School Division A, and they were considered *data missing not at random* (Newman, 2014). For data missing not at random, Newman (2014) advised a deeper consideration of these cases based on available data to avoid a biased listwise deletion of summarily removing students from the sample who had missing data. Of the students with a missing GPA, 54 were coded as an on-time graduate but did not have a grade from any School-Division-A course; it was assumed that these students attended and graduated from a non-School-Division-A school (e.g., regional public academy, special education private placement, etc.) and were assigned to School Division A by the VDOE for accountability and reporting purposes; these students were removed from the sample. There were 115 students with a missing GPA who took a School-Division-A course and received a grade that resulted in no points being assigned (i.e., "I," "N," "NC," "P," "W," and "WP"). These students were included in the sample

and were assigned a GPA of 0.00. After the removal of the 54 students from the sample, 10,010 students remained in the sample.

School Division A identified online courses; any course with the same SCED code as an online course was coded as being *connected to an online course*. For the variable *eligible*, students who took a connected course and failed that course were identified as *eligible for online credit recovery*; students who never failed a connected course were identified as *not eligible* (0). For the variable *participation*, students who were eligible and who after took a connected online course were identified as *participating in online credit recovery* (1); students who did not take such an online course, or those who did not fail an eligible course, were identified as *did not participate* (0). For the variable *participation groups*, students were coded as students who were *never eligible for online credit recovery* (0), students who were *eligible for, but did not participate in, online credit recovery* (1), and students who *participated in online credit recovery* (2).

Description of the Sample

There were 10,010 students in the sample, all from School Division A. For the categories of race and ethnicity, 4933 students were White, 2732 students were Black, 1551 students were Hispanic, 416 students were two or more races, 352 students were Asian, 15 students were American Indian or Alaska native, and 11 students were Native Hawaiian or Other Pacific Islander. There were 5242 males and 4767 females. Overall, 11.3% of students in the sample were SWD, 6.5% were EL, and 1.5% were homeless. In total, School Division A reported that 93% of students in the sample graduated on time. Table 6 highlights descriptive frequencies of students in the sample.

Table 6

Descriptive Frequencies of Sample

Student Characteristic	*n*	%
American Indian or Alaska Native	15	0.1
Asian	352	3.5
Black or African American	2732	27.3
Hispanic	1551	15.5
Native Hawaiian or Other Pacific Islander	11	0.1
Two or more races	416	4.2
White	4933	49.3
Female	4767	47.6
Male	5243	52.4
SWD	1134	11.3
Not SWD	8876	88.7
EL	648	6.5
Not EL	9362	93.5
Homeless	151	1.5
Not Homeless	9859	98.5
On-Time Graduate	9308	93.0
Did not graduate on time	702	7.0

Note. School Division A did not provide information about student status as economically disadvantaged.

There were 11 high schools in School Division A, identified as School 0 through School 10 for confidentiality. School 0 had 291 students with 71.1% of them graduating on time, and School 0 accounted for 12.0% of students who did not graduate on time from School Division A in 2019 and 2020. School 1 had 957 students with 97.2% of them graduating on time, and School 1 accounted for 3.8% of students who did not graduate on time. School 2 had 1121 students with 99.5% of them graduating on time, and School 2 accounted for 0.9% of students who did not graduate on time. School 3 had 1046 students with 92.4% of them graduating on time, and School 3 accounted for 11.4% of students who did not graduate on time. School 4 had 924 students with 90.7% of them graduating on time, and School 4 accounted for 12.3% of students who did not graduate on time. School 5 had 1013 students with 94.0% of them graduating on time, and School 5 accounted for 8.7% of students who did not graduate on time. School 6 had 872 students with 95.0% of them graduating on time, and School 6 accounted for 6.3% of students who did not graduate on time. School 7 had 972 students with 78.7% of them graduating on time, and School 7 accounted for 29.5% of students who did not graduate on time. School 8 had 833 students with 98.8% of them graduating on time, and School 8 accounted for 1.4% of students who did not graduate on time. School 9 had 749 students with 95.0% of them graduating on time, and School 9 accounted for 5.4% of students who did not graduate on time. School 10 had 1232 students with 95.2% of them graduating on time, and School 10 accounted for 8.5% of students who did not graduate on time. Overall, 82.3% of students who did not graduate on time came from six schools – Schools 0, 3, 4, 5, 7, and 10. Table 7 shows each school, their total number of students, their total number of on-time graduates, and their total number of not-on-time graduates; furthermore, percentages of the division total are given for each *n* value.

Table 7

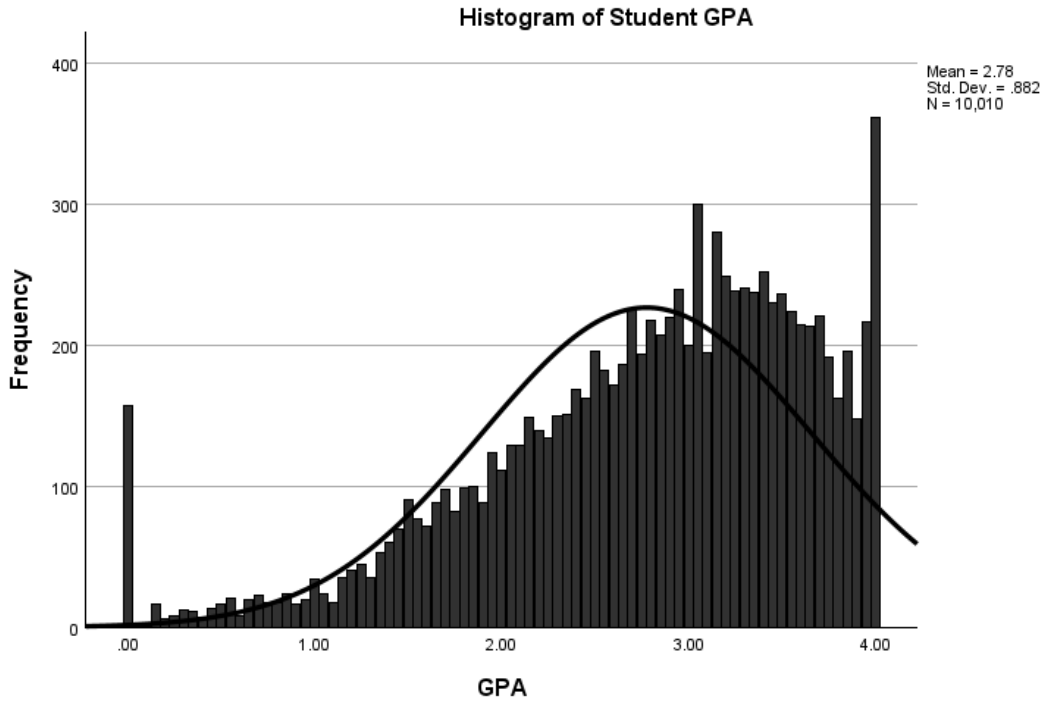
Crosstabulation of School and On-Time Graduation

School	Not On-Time Graduate		On-Time Graduate	
	n	%	*n*	%
School 0	84	12.0	207	2.2
School 1	27	3.8	930	10.0
School 2	6	0.9	1115	12.0
School 3	80	11.4	966	10.4
School 4	86	12.3	838	9.0
School 5	61	8.7	952	10.2
School 6	44	6.3	828	8.9
School 7	207	29.5	765	8.2
School 8	10	1.4	823	8.8
School 9	38	5.4	711	7.6
School 10	59	8.4	1173	12.6

Student GPA was a continuous variable that contained values from 0.00 to 4.00, inclusive. The mean GPA was 2.78 with a standard deviation of 0.88. Half of the GPAs in the sample were between 2.26 and 3.45. The most common GPA was 4.00 with 3.6% of students having this value; GPAs of 3.00 (1.8%), 0.00 (1.6%), 2.00 (1.1%), 3.07 (1.0%), and 3.50 (1.0%) each accounted for between 1.0% and 2.0% of GPAs. All other GPAs occurred less frequently than 1.0%. The skewness of the data was -0.91 and kurtosis was 0.63. A histogram of GPAs is shown in Figure 3.

Figure 3

Histogram of Student GPA



Data Analysis

Research Question 1

Research Question 1 was "what were factors that explained student participation in online credit recovery" with the following null and alternative hypotheses:

- H_0: $\beta_1 = \beta_2 = \beta_n = 0$. No independent variable was associated with participation in online credit recovery; no variable coefficient was statistically significant in the model.
- H_A: Some $\beta_i \neq 0$. At least one independent variable explained participation in online credit recovery because at least one variable coefficient was statistically significant in the model.

Initially, contingency tables were considered to see how participation in online credit recovery varied among student factors and school. A logistic model was then built following the Hosmer et al. (2013) framework to test hypotheses.

Descriptive Statistics. Of the students in the sample, 230 students, or 2.3% of the sample, participated in online credit recovery. When considering categories of race and ethnicity, 49.1% of participants were White, 26.5% were Black, 18.3% were Hispanic, and 5.2 % were two or more races. When comparing the rate of participation with the proportion of the sample, only Hispanic (18.3% participation, 15.5% of the total sample) and two or more races (5.2% participation, 4.2% of the total sample) had higher participation rates. Similarly, higher rates of participation were found in gender where 60.9% of participants were male and in SWD where 20.4% of the participants were SWD. Lower rates of participation were found with female students (39.1%), EL (4.8%), and homeless. Overall, no category had a participation rate of more or less than 10 percentage points of their proportion of the sample. Of students who did not graduate on time, 5.6% participated in online credit recovery; Of students who did graduate on time, 2.1% participated in online credit recovery. Table 8 shows a contingency table for participation in online credit recovery counts and student factors.

Table 8

Participation in Online Credit Recovery and Student Factors

Student Characteristic	Did Not Participate		Participated		Total	
	n	%	*n*	%	*n*	%
American Indian or Alaskan Native [a]					15	0.1
Asian [a]					352	3.5

Student Characteristic	Did Not Participate		Participated		Total	
	n	%	*n*	%	*n*	%
Black or African American	2671	27.3	61	26.5	2732	27.3
Hispanic	1509	15.4	42	18.3	1551	15.5
Native Hawaiian or Other Pacific Islander [a]					11	0.1
Two or more races	404	4.1	12	5.3	416	4.2
White	4820	49.3	113	49.1	4933	49.3
Female	4677	47.8	90	39.1	4767	47.6
Male	5103	52.2	140	60.9	5243	52.4
SWD	1087	11.1	47	20.4	1134	11.3
Not SWD	8693	88.9	183	79.6	8876	88.7
EL	637	6.5	11	4.8	648	6.5
Not EL	9143	93.5	219	95.2	9362	93.5
Homeless [a]					151	1.5
Not Homeless [a]					9859	98.5

Note. School Division A did not provide information about student status as economically disadvantaged.

[a] One of the categories for this characteristic had a count of $n < 10$ and was below the threshold for reporting (National Center for Educational Statistics [NCES], 2010).

Student participation counts were also considered by school (see Table 9). Five schools—Schools 1, 3, 4, 5, and 10—comprised 62.7% of the participants in online credit recovery. Two schools—Schools 2 and 8—each had fewer than 10 participants and accounted for 7.4% of

participants combined. School 0 had the largest proportion of their students participate in online credit recovery; 6.5% of the students at School 0 participated in online credit recovery. School 6 accounted for 8.3% of the participants, School 7 accounted for 7.0% of the participants, and School 9 accounted for 6.5% of the participants.

Table 9

Schools and Participation in Online Credit Recovery

School	Did Not Participate		Participated		Total	
	n	%	*n*	%	*n*	%
School 0	272	2.8%	19	8.3%	291	2.9%
School 1	932	9.5%	25	10.9%	957	9.6
School 2 [a]					1121	11.2
School 3	1015	10.4	31	13.5	1046	10.4
School 4	896	9.2	28	12.2	924	9.2
School 5	984	10.1	29	12.6	1013	10.1
School 6	853	8.7	19	8.3	872	8.7
School 7	956	9.8	16	7.0	972	9.7
School 8 [a]					833	8.3
School 9	734	7.5	15	6.5	749	7.5
School 10	1201	12.3	31	13.5	1232	12.3

[a] One of the categories for this school had a count of $n < 10$ and was below the threshold for reporting (NCES, 2010).

Table 10 shows the distribution of GPAs for each category in the variable *participate* using the quartiles of the overall variable GPA. Of the students who participated in online credit recovery, 83.0% had a GPA in the first quartile, 3.5% had a GPA in the third quartile, and 0.0% had a GPA in the fourth quartile. Of the students who did not participate, 23.5% had a GPA in the first quartile, 26.3% had a GPA in the third quartile, and 25.2% had a GPA in the fourth quartile. The mean GPA for a student who participated in online credit recovery was 1.63 with a standard deviation of 0.67. The mean GPA for a student who did not participate was 2.80 with a standard deviation of 0.87.

Table 10

GPAs by Participation in Online Credit Recovery

GPA	Did Not Participate		Participated	
	n	%	*n*	%
Q1: 0.00-2.25	2299	23.5	191	83.0
Q2: 2.26-2.92	2447	24.8	31	13.5
Q3: 2.93-3.45	2572	26.5	8	3.5
Q4: 3.46-4.00	2462	25.2	0	0.0

Regression Model. For Research Question 1, a binary logistic regression model was developed with a dependent variable of participation in online credit recovery using the Hosmer et al. (2013) framework. Explanatory variables from Tables 8, 9, and 10 were considered for inclusion in the initial logistic regression model, and crosstabulation values of under 16 were considered for removal or collapse (Orme & Combs-Orme, 2009; see also Hosmer et al., 2013).

In the categories of race and ethnicity, participation counts for American Indian or Alaskan Native, Asian, Native Hawaiian or Other Pacific Islander, and two or more races were all below the threshold of 16—they were collapsed into a single race and ethnicity category. In the categories of schools, participation counts for Schools 2, 8, and 9 were all below 16—they were collapsed into a single school category. Participation counts for EL and Homeless were also below 16; however, because they were greater than zero and there was no alternative way to collapse, each variable remained unchanged (Hosmer et al., 2013).

These variables were deemed appropriate for inclusion in the initial model (Bursac et al., 2008; Hosmer et al., 2013). The confidence level for the model was set at 95% ($\alpha = .05$). The initial model produced the Omnibus Tests of Model Coefficients $\chi^2(18) = 381.350$, $p < .001$. The Hosmer and Lemeshow Test was significant with $\chi^2(8) = 21.546$, $p = .006$. The Nagelkerke R Square value was .190. The initial model indicated that the variables of gender ($p = .383$) and SWD ($p = .765$) were not significant, and these variables were selected for removal for the second model. The initial model indicated that the variable homeless ($p = .056$) was not significant; however, because it was close to $p = .05$, it was included in the second model to see if it became significant with the removal of gender and SWD.

The second model included the variables of race and ethnicity, school, status as EL, status as homeless, and GPA. The second model produced the Omnibus Tests of Model Coefficients $\chi^2(14) = 380.445$, $p < .001$. The Hosmer and Lemeshow Test was significant with $\chi^2(8) = 23.130$, $p = .003$. The Nagelkerke R Square value remained .190. The second model also indicated that the category of homeless ($p = .060$) was not significant. Because this variable was not significant for both models and the value for the second model was higher than that of the first model, the variable homeless was selected for removal for the third model.

The third model included the variables of race and ethnicity, school, status as EL, and GPA. The third model produced the Omnibus Tests of Model Coefficients $\chi^2(12) = 357.823$, $p < .001$. The Hosmer and Lemeshow Test was still significant with $\chi^2(8) = 25.341$, $p = .001$. Furthermore, the Nagelkerke R Square value decreased to .187. All variables in Model 3 were significant, and no additional variables were available to be added to the next model (Hosmer et al., 2013).

Because Model 3 had a significant Hosmer and Lemeshow test, combinations of the variables in Model 3—race and ethnicity, school, GPA, and status as EL—were examined to see if any model met established goodness of fit standards (see Table 11; Hosmer et al., 2013). Only one such model—race and ethnicity, school, and status as EL—met the standards. This fourth model produced the Omnibus Tests of Model Coefficients $\chi^2(12) = 47.772$, $p < .001$. The Hosmer and Lemeshow Test was not significant with $\chi^2(7) = 13.273$, $p = .066$. The Nagelkerke R Square value decreased to .024. Model 4 became the main effects model.

Table 11

Goodness of Fit Values for Logistic Regression Models for Participation

Model	Omnibus Tests of Model Coefficients	Hosmer and Lemeshow Test	Nagelkerke R Square
Model 1	381.350***	21.546*	.190
Model 2	380.445***	23.130*	.190
Model 3	357.823***	25.341*	.187
Model 4	47.772***	13.273	.024

Note. $N = 10{,}010$. Significance was set at $\alpha = .05$ level.

*$p < .05$. ***$p < .001$.

Possible interactions were checked by adding them individually to Model 4 to see if the interaction variable was statistically significant. Three such interactions were checked – race * school (p = .071), race * EL (p = 1.00), and school * EL (p = .902). Because no interaction variable was significant $p < .05$, Model 4 was selected as the preliminary final model.

As the preliminary final model, Model 4 was checked for fit and adequacy. Three issues were identified with fit. First, Hosmer et al. (2013) advised that the Hosmer and Lemeshow test (a) be not significant and (b) have a standardized difference of observed and expected of at least 2.0 for the decile with the largest absolute difference between observed and expected. The Hosmer and Lemeshow test for Model 4 was not significant with $p = .066 > .05$; however, the measured standardized difference was 1.53, smaller than 2.00. This indicated that the p-value may be lower than p = .066, and the Hosmer and Lemeshow Test may actually be overcalculating the actual value (Hosmer et al., 2013). This concern showed that the Hosmer and Lemeshow Test may actually be significant $p < .05$. Table 12 shows the contingency table for the Hosmer and Lemeshow Test.

Table 12

Contingency Table for the Hosmer and Lemeshow Test for Model 4

Decile	Did Not Participate		Participated		Absolute Difference	Standardized Difference
	Observed	Expected	Observed	Expected		
1	988	990.34	13	10.67	2.33	0.71
2	1761	1757.46	18	21.54	3.54	0.76
3	996	1004.96	26	17.04	8.96	2.16

Decile	Did Not Participate		Participated		Absolute Difference	Standardized Difference
	Observed	Expected	Observed	Expected		
4	1046	1043.11	20	22.89	2.89	0.60
5	925	915.78	13	22.22	9.22	1.96
6	819	817.11	20	21.89	1.89	0.40
7	1037	1036.51	29	29.49	0.49	0.09
8	1122	1118.00	31	35.00	4.00	0.68
9	1086	1096.73	60	49.27	10.73	1.53

Note. For checking the reliability of the significance of the Hosmer and Lemeshow Test, the standardized difference for the decile with the largest absolute difference was used (Hosmer et al., 2013).

Second, the Nagelkerke R Square for Model 4 was .024, below the recommended .30 for predictive purposes (Glynn, 2010). Third, sensitivity could not be calculated for Model 4 because no student was identified by the model as participated in online credit recovery. Model 4 misclassified all students who participated in online credit recovery. Table 13 gives a classification table of Model 4 for predicted and observed values.

Table 13

Classification Table of Predicted and Observed for Model 4

Observed	Predicted	
	Did Not Participate (0)	Participated (1)
Did Not Participate (0)	9780	0
Participated (1)	230	0

Note. Sensitivity was unable to be calculated. Specificity = 9780 / 10010, 97.70%

Because of the multiple concerns with the fit of Model 4, it was rejected as a model that fits the data. The lack of a model to test the significance of variable coefficients justified a failure to reject the null hypothesis of Research Question 1. It was possible that no collected explanatory variable, or interaction of explanatory variables, explained participation in online credit recovery.

Research Question 2

Research Question 2 was "how much more or less likely were students who participated in online credit recovery to graduate high school on time compared to (a) the likelihood of those who were eligible for but did not participate in online credit recovery and (b) the likelihood of those who were never eligible for online credit recovery" with the following initial hypotheses:

- H_0: $\beta_{\text{Group Participation}} = 0$. The coefficient for the independent variable of group participation was not statistically significant in the model.
- H_A: $\beta_{\text{Group Participation}} \neq 0$. The coefficient for the independent variable of group participation was statistically significant in the model.

If the initial null hypothesis were rejected, two cases would have then been considered comparing the group of participants against the other two groups. The first case would have

compared the participant group with the group that was never eligible for online credit recovery. The hypotheses for this case were:

- H_0: $\beta_{NotEligible} = \beta_{Participated}$. There was no statistically-significant difference between the coefficient for those who were never eligible for online credit recovery and those who participated in online credit recovery.
- H_A: $\beta_{NotEligible} \neq \beta_{Participated}$. There was a statistically-significant difference between the coefficient for those who never eligible in online credit recovery and those who participated in online credit recovery.

The second case would have compared the participant group with the group that was eligible for, but did not participate in, online credit recovery. The hypotheses for this case were:

- H_0: $\beta_{EligibleDNP} = \beta_{Participated}$. There was no statistically-significant difference between the coefficient for those who were eligible for but did not participate in online credit recovery and those who participated in online credit recovery.
- H_A: $\beta_{EligibleDNP} \neq \beta_{Participated}$. There was a statistically-significant difference between the coefficient for those who were eligible for but did not participate in online credit recovery and those who participated in online credit recovery.

Initially, contingency tables were considered to see how on-time graduation varied among student factors, participation group, and school. A logistic model was then built following the Hosmer et al. (2013) framework to test hypotheses.

Descriptive Statistics. Of the students in the sample, 7306 students (73.0%) were never eligible for participation in online credit recovery, and 2704 students (27.0%) were eligible to participate in online credit recovery. Of those who were eligible, 2474 students (91.5%) did not participate in online credit recovery, and 230 students (8.5%) participated in online credit

recovery. Categories for the variable *participation group* were 73.0% of students were never eligible for participation, 24.7% of students were eligible for participation but did not participate, and 2.3% of students participated. Of those who did not graduate on time, 15.2% participated in online credit recovery. Of those who graduated on time, 2.7% participated in online credit recovery. Of students who participated in online credit recovery, 83.0% graduated on time. Table 14 shows the count of students based on their assigned participation group.

Table 14

Students based on Participation Group and On-Time Graduation

Participation Group	Not On-Time Graduate		On-Time Graduate	
	n	%	*n*	%
Not Eligible	256	36.5	7050	75.7
Eligible				
Did Not Participate	407	58.0	2067	22.2
Participated	39	5.6	191	2.1

Note. N = 10,010.

When considering categories race and ethnicity, White students comprised 54.1% of those not eligible, 35.2% of those eligible but did not participate, and 49.1% of those who participated in online credit recovery. Black students were the second largest category, comprising 24.0% of those not eligible, 37.2% of those eligible but did not participate, and 26.5% of those who participated in online credit recovery. Hispanic students comprised 13.3% of those not eligible, 21.8% of those eligible but did not participate, and 18.3% of those who participated in online credit recovery. Two or more races comprised 4.2% of those not eligible,

3.8% of those eligible but did not participate, and 5.2% of those who participated. There were at least nine or fewer students in at least one category for American Indian or Alaskan Native, Asian, and Native Hawaiian or Other Pacific Islander, and their participation counts were not reported (NCES, 2010).

For other student factors, male students comprised 48.4% of those not eligible for online credit recovery, but they comprised over 60% of both eligible but did not participate and participated in online credit recovery. Students identified as SWD comprised larger proportions of the eligible but did not participate and participated in online credit recovery categories (19.8% and 20.4%, respectively) than not eligible (8.2%). For EL students, they comprised 5.1% of students not eligible for online credit recovery, 10.5% of those eligible but did not participate, and 4.8% of those who participated in online credit recovery. There were at least nine or fewer students in at least one category for homeless students, and their participation counts were not reported (NCES, 2010). Table 15 shows the count of students based on student factors and their participation group.

Table 15

Student Factors and Classification by Participation Group

Student Characteristic	Not Eligible		Eligible, but Did Not Participate		Participated	
	n	%	*n*	%	*n*	%
American Indian or Alaskan Native [a]						
Asian[a]						
Black or African American	1750	24.0	921	37.2	61	26.5
Hispanic	969	13.3	540	21.8	42	18.3

Student Characteristic	Not Eligible		Eligible, but Did Not Participate		Participated	
	n	%	*n*	%	*n*	%
Native Hawaiian or Other Pacific Islander [a]						
Two or more races	310	4.2	94	3.8	12	5.2
White	3950	54.1	870	35.2	113	49.1
Female	3770	51.6	907	36.7	90	39.1
Male	3536	48.4	1567	63.3	140	60.9
SWD	597	8.2	490	19.8	47	20.4
Not SWD	6709	91.8	1984	80.2	183	79.6
EL	376	5.1	261	10.5	11	4.8
Not EL	6930	94.9	2213	89.5	219	95.2
Homeless [a]						
Not Homeless [a]						

Note. School Division A did not provide information about student status as economically disadvantaged.

[a] One of the categories for this characteristic had a count of $n < 10$ and was below the threshold for reporting (NCES, 2010).

Table 16 shows the distribution of students in a given school across the three participation groups. Schools 0, 4, 5, and 10 all formed a larger proportion of students in both the *eligible but did not participate* group and *participated* group than the *not eligible* group.

Furthermore, 54.1% of the *eligible but did not participate* group came from four schools – School 4 (12.0%), School 5 (13.0%), School 7 (15.9%), and School 10 (13.2%).

Table 16

School and Classification by Participation Group

School	Not Eligible		Eligible, but Did Not Participate		Participated	
	n	%	*n*	%	*n*	%
School 0	106	1.5	166	6.7	19	8.3
School 1	749	10.3	183	7.4	25	10.9
School 2 [a]	1044	14.3				
School 3	778	10.6	237	9.6	31	13.5
School 4	600	8.2	296	12.0	28	12.2
School 5	663	9.1	321	13.0	29	12.6
School 6	637	8.7	216	8.7	19	8.3
School 7	563	7.7	393	15.9	16	7.0
School 8 [a]	718	9.8				
School 9	574	7.9	160	6.5	15	6.5
School 10	874	12.0	327	13.2	31	13.5

[a] One of the categories for this school had a count of $n < 10$ and was below the threshold for reporting (NCES, 2010).

Table 17 shows the distribution of GPAs for each group using the quartiles of the overall GPA variable. Of the students who participated in online credit recovery, 83.0% had a GPA in

the first quartile, 3.5% had a GPA in the third quartile, and 0.0% had a GPA in the fourth quartile. Of the students who were eligible but did not participate, 71.1% had a GPA in the first quartile, 3.7% had a GPA in the third quartile, and 0.3% had a GPA in the fourth quartile. Of the students who were never eligible, 7.4% had a GPA in the first quartile, 33.9% had a GPA in the third quartile, and 33.6% had a GPA in the fourth quartile. The mean GPA for a student who participated in online credit recovery was 1.36 with a standard deviation of 0.67. The mean GPA for a student who was eligible but did not participate was 1.87 with a standard deviation of 0.68. The mean GPA for a student who was never eligible was 3.12 with a standard deviation of 0.67.

Table 17

GPAs by Participation Group

GPA	Not Eligible		Eligible, but Did Not Participate		Participated	
	n	%	*n*	%	*n*	%
Q1: 0.00-2.25	541	7.4	1758	71.1	191	83.0
Q2: 2.26-2.92	1830	25.0	617	24.9	31	13.5
Q3: 2.93-3.45	2480	33.9	92	3.7	8	3.5
Q4: 3.46-4.00	2455	33.6	7	0.3%	0	0.0%

Regression Model. For Research Question 2, a binary logistic regression model was developed with a dependent variable of on-time graduation and independent variable of participation group using the Hosmer et al. (2013) framework. Explanatory variables from Tables 15, 16, and 17 were considered for inclusion in the initial logistic regression model, and

crosstabulation values of under 16 were considered for removal or collapse (Orme & Combs-Orme, 2009; see also Hosmer et al., 2013).

In the categories of race and ethnicity, participation counts for American Indian or Alaskan Native, Asian, Native Hawaiian or Other Pacific Islander, and two or more races were all below the threshold of 16 – they were collapsed into a single race and ethnicity category. In the categories of schools, participation counts for Schools 2, 8, and 9 were all below 16—they were collapsed into a single school category. Participation counts for EL and Homeless were also below 16; however, because they were greater than zero and there was no alternative way to collapse, each variable remained unchanged and included (Hosmer et al., 2013).

These variables were deemed appropriate for inclusion in the initial model (Hosmer et al., 2013). The confidence level for the model was set at 95% ($\alpha = 0.05$). The initial model produced the Omnibus Tests of Model Coefficients $\chi^2(18) = 2552.065$, $p < .001$. The Hosmer and Lemeshow Test was significant with $\chi^2(8) = 23.904$, $p = .002$. The Nagelkerke R Square value was .565. The initial model indicated that the categories of gender ($p = .350$) and SWD ($p = .237$) were not significant, and these variables were selected for removal for the second model. The initial model indicated that the category homeless ($p = .055$) was not significant; however, because it was close to $p = .05$, it was included in the second model to see if it became significant with the removal of gender and SWD.

The second model included the variables of participation group, race and ethnicity, school, status as EL, status as homeless, and GPA. The second model produced the Omnibus Tests of Model Coefficients $\chi^2(16) = 2549.945$, $p < .001$. The Hosmer and Lemeshow Test was significant with $\chi^2(8) = 26.769$, $p < .001$. The Nagelkerke R Square value remained .565. The second model also indicated that the category of Homeless ($p = .046$) became significant. While

all variables were significant $p < .05$, the Hosmer and Lemeshow Test was significant ($p < .001$), and variables were considered for exclusion in the next model (Hosmer et al., 2013). Both participation group and GPA showed significance $p < .001$ in Model 2; however, Table 17 indicated that there is a relationship between the two variables, and GPA was chosen for removal for Model 3 (Hosmer et al., 2013).

The third model included the variables of participation group, race and ethnicity, school, status as EL, and status as homeless. The third model produced the Omnibus Tests of Model Coefficients $\chi^2(15) = 1161.027$, $p < .001$. The Hosmer and Lemeshow Test was significant with $\chi^2(8) = 59.062$, $p < .001$. The Nagelkerke R Square value decreased to .275. All remaining categories were significant, $p < .05$.

Because Model 3 had a significant Hosmer and Lemeshow test, combinations of the variables in Model 3—race and ethnicity, school, status as EL, and status as homeless—were examined to see if any model met established goodness of fit standards (Hosmer et al., 2013). Each combination produced significant results on the Hosmer and Lemeshow Test, $p < .001$ (see Table 18).

Table 18

Goodness of Fit Values for Logistic Regression Models for On-Time Graduation

Model	Omnibus Tests of Model Coefficients	Hosmer and Lemeshow Test	Nagelkerke R Square
Model 1	2552.065***	23.904*	0.565
Model 2	2549.945***	26.769***	0.565
Model 3	1161.027***	59.062***	0.275

Model	Omnibus Tests of Model Coefficients	Hosmer and Lemeshow Test	Nagelkerke R Square
Model 3 − School	987.095***	42.273***	0.236
Model 3 − Homeless	1144.687***	54.249***	.271
Model 3 − EL	1001.544***	53.675***	.239
Model 3 − Race	1139.074***	53.813***	.270

Note. N = 10,010. Significance was set at $\alpha = 0.05$ level.

*$p < .05$. ***$p < .001$.

While no model had a not significant Hosmer and Lemeshow test, Model 1 was chosen as the main effects model because it had (a) the p-value closest to $p = .05$ and (b) a Nagelkerke R Square value greater than or equal to all other models. Model 1 was then checked for interactions for significant interaction variables at the $\alpha = 0.05$ level (Hosmer et al., 2013); there were 28 such interactions that were checked, and 16 were not significant at the $p \geq .10$ level. These 16 interactions were excluded from consideration in the preliminary final model.

There were 12 interaction variables where the variable was $p < .10$. Their significance and their resulting Hosmer and Lemeshow Test value for their model were used to consider their inclusion in the preliminary final model. Seven interaction variables were significant at the $p < .001$ level; however, their corresponding Hosmer and Lemeshow Test values were also significant at the $p < .001$ level. Those variables were excluded from the preliminary model. One interaction variable, Gender * GPA, was significant at $p = .007$; however, the resulting Hosmer

and Lemeshow Test value $\chi^2(8) = 44.720$, $p < .001$, and this interaction variable was excluded from the preliminary final model.

The remaining four interaction variables showed $p < .10$ when individually added to Model 1; however, their models also had a significant Hosmer and Lemeshow Test value at $p < .01$. Each of the four models with one of these interaction variables also had a Nagelkerke R Square value greater than .500. The significance, Hosmer and Lemeshow Test values, and Nagelkerke R Square values for these interaction variables and their models are shown in Table 19.

Table 19

Goodness of Fit Values for Regression Models Including Interaction Variables

Interaction Variable Added to Model 1	Significance of Interaction Variable	Hosmer and Lemeshow Test	Nagelkerke R Square
Participation Group * GPA	$p < .001$***	24.594**	.568
Race * SWD	$p = .060$	23.721**	.567
Gender * Homeless	$p = .088$	20.792**	.566
Gender * GPA	$p = .007$**	29.620***	.566
SWD * EL	$p = .014$*	22.991**	.566

Note. $N = 10{,}010$. Significance was set at $\alpha = 0.05$ level.

*$p < .05$. **$p < .01$. ***$p < .001$.

To form the final preliminary final model, 31 combinations of these five interaction variables were considered for inclusion with the eight variables from the main effects model, Model 1. Consideration of the best model was based on (a) a significant Omnibus Tests of Model Coefficients, (b) a not significant Hosmer and Lemeshow Test, and (c) a Nagelkerke R Square value of at least .500. Five models were examined in Table 17, each containing the variables of Model 1 and a single interaction variable. Twenty-six other models were considered consisting of the variables from Model 1 and combinations of multiple interaction variables.

All 31 models had significant Omnibus Tests of Model Coefficients at the $p < .001$ level as well as Nagelkerke R Square values of .567 or higher. However, only seven models had a Hosmer and Lemeshow Test value with significance $.02 < p < .05$, and none were not significant at the $p = .05$ level (see Table 20). The model with all interaction variables—Participation Group * GPA, Race * SWD, Gender * Homeless, Gender * GPA, and SWD * EL—had a Hosmer and Lemeshow Test value of $\chi^2(8) = 16.767$, $p = .033$. The model with interaction variables Participation Group * GPA, Race * SWD, Gender * Homeless, and Gender * GPA had a Hosmer and Lemeshow Test value of $\chi^2(8) = 17.500$, $p = .025$. The model with interaction variables Participation Group * GPA, Race * SWD, Gender * Homeless, and SWD * EL had a Hosmer and Lemeshow Test value of $\chi^2(8) = 18.038$, $p = .021$. The model with interaction variable Participation Group * GPA, Race * SWD, Gender * GPA, and SWD * EL had a Hosmer and Lemeshow Test value of $\chi^2(8) = 17.633$, $p = .024$. The model with interaction variables Participation Group * GPA, Race * SWD, and Gender * Homeless had a Hosmer and Lemeshow Test value of $\chi^2(8) = 17.181$, $p = .028$. The model with interaction variables Participation Group * GPA, Race * SWD, and Gender * GPA had a Hosmer and Lemeshow Test value of $\chi^2(8) = 17.452$, $p = .026$. The model with interaction variables Participation Group * GPA and Race *

SWD had a Hosmer and Lemeshow Test value of $\chi^2(8) = 17.106$, $p = .029$. Table 20 shows the goodness of fit values for the models with interaction variable combinations that produced Hosmer and Lemeshow Test statistics with $.02 < p < .05$.

Table 20

Goodness of Fit Values for Models with Hosmer and Lemeshow Tests .02 < p < .05

Interaction Variables Added to Model 1	Omnibus Tests of Model Coefficients	Hosmer and Lemeshow Test	Nagelkerke R Square
Participation Group * GPA, Race * SWD, Gender * Homeless, Gender * GPA, and SWD * EL	2584.790***	16.767*	.571
Participation Group * GPA, Race * SWD, Gender * Homeless, and Gender * GPA	2583.183***	17.500*	.571
Participation Group * GPA, Race * SWD, Gender * Homeless, and SWD * EL	2580.972***	18.038*	.571
Participation Group * GPA, Race * SWD, Gender * GPA, and SWD * EL	2581.359***	17.633*	.571
Participation Group * GPA, Race * SWD, Gender * Homeless	2578.887***	17.181*	.570
Participation Group * GPA, Race * SWD, Gender * GPA	2579.564***	17.452*	.570
Participation Group * GPA, Race * SWD	2575.642***	17.106*	.570

Note. N = 10,010. Significance was set at $\alpha = 0.05$ level.

*$p < .05$. **$p < .01$. ***$p < .001$.

With a significant Omnibus Tests of Model Coefficients and a Nagelkerke R Square value of .571, the model combining the variables of Model 1 and all five interaction variables had a Hosmer and Lemeshow Test of $\chi^2(8) = 16.767$, $p = .033$. While significant $p < .05$, it was the closest to $p = .05$. For this model, the value for the Nagelkerke R Square value (.571) was also greater than or equal to the value of any other model generated. This model was selected as the preliminary final model.

The preliminary final model was checked for fit and adequacy. The Omnibus Tests of Model Coefficients was significant $p < .001$. The Nagelkerke R Square value was greater than .30, allowing the model to be used for predictive purposes (Glynn, 2010). The sensitivity and specificity of model were both over 75%, and Table 21 shows the classification table of predicted and observed for Model 4.

Table 21

Classification Table of Predicted and Observed for Preliminary Final Model

Observed	Predicted		Percentage Correct
	Not On-Time Graduate	On-Time Graduate	
Not On-Time Graduate	366	336	52.1
On-Time Graduate	110	9198	98.8

Note. Sensitivity = 9198 / 9534 = 96.48. Specificity = 366 / 476 = 76.89%

However, two issues were identified with fit. Hosmer et al. (2013) advised that the Hosmer and Lemeshow test (a) be not significant and (b) have a standardized difference of observed and expected of at least 2.0 for the decile with the largest absolute difference between

observed and expected. The Hosmer and Lemeshow test for the preliminary final model was significant with $p = .033$, and the measured standardized difference was 0.86, smaller than 2.00 (see Table 22). This indicated that the p-value may be lower than $p = .033$ (Hosmer et al., 2013).

Table 22

Contingency Table for the Hosmer and Lemeshow Test—Preliminary Final Model

Decile	Not On-Time Graduate		On-Time Graduate		Absolute Difference	Standardized Difference
	Observed	Expected	Observed	Expected		
1	543	524.12	458	476.88	18.88	0.86
2	80	92.84	921	908.16	12.84	1.33
3	24	35.26	977	965.74	11.26	1.90
4	21	18.78	980	982.22	2.22	0.51
5	10	11.80	991	989.20	1.80	0.52
6	7	7.60	994	993.40	0.60	0.22
7	6	5.04	995	995.96	0.96	0.43
8	3	3.30	998	997.70	0.30	0.16
9	4	2.11	997	998.89	1.89	1.30
10	4	1.14	997	999.86	2.86	2.68

Note. For checking the reliability of the significance of the Hosmer and Lemeshow Test, the standardized difference for the decile with the largest difference is used (Hosmer et al., 2013).

Because of the Hosmer and Lemeshow Test concerns on the fit of the preliminary final model, it was rejected as a model that fits the data. The lack of a model to test the significance of variable coefficients justified a failure to reject the initial null hypothesis of Research Question 2.

It was possible that a student's eligibility for or participation in online credit recovery did not increase or decrease the likelihood of a student's on-time graduation.

Summary

The purpose of this study was (a) to identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) to identify the likelihood of on-time graduation of students who participated in online credit recovery compared to those who did not participate, including those who were never eligible to participate and those who were eligible for, but did not participate in, online credit recovery. Three large divisions were invited to participate in the study. School Divisions A and B agreed to participate, and data was received from School Division A.

Collected data was cleaned using qualitative data cleaning techniques (Ilyas & Chu, 2019), and additional variables were calculated from the collected data. Categorical variables were coded with an integer. There were 10,010 students in the sample; 230 students participated in online credit recovery, and 9308 students graduated on time.

Research Question 1 sought to identified factors that explained student participation in online credit recovery. A binary logistic regression model with a dependent variable of participation in online credit recovery was developed using an iterative framework (Hosmer et al., 2013). The preliminary final model included explanatory factors of race and ethnicity, school, and status as EL. The model had a significant Omnibus Tests of Model Coefficient ($p < .001$); however, three issues with the model fit were identified. The Hosmer and Lemeshow Test was possibly significant, the Nagelkerke R Square value was below .30, and sensitivity was unable to be calculated. No model was identified as fitting the data, justifying a failure to reject the null hypothesis of Research Question 1.

Research Question 2 sought to determine how much more or less likely a student who participated in online credit recovery would have graduated on time compared to students who did not participate, both those who were never eligible and those who were eligible to participate but did not. A binary logistic regression model with a dependent variable of on-time graduation, an independent variable of participation group (never eligible, eligible but did not participate, and participated), and explanatory variables of student factors was developed using an iterative framework (Hosmer et al., 2013). In addition to the dependent and independent variables, the preliminary final model had explanatory variables of school, race and ethnicity, gender, status as EL, status as SWD, status as homeless, and GPA. The preliminary final model had interaction variables participation group * GPA, race and ethnicity * status as SWD, gender * status as homeless, gender * GPA, and status as SWD * status as EL. The model had a significant Omnibus Tests of Model Coefficient ($p < .001$) and the Nagelkerke R Square value was above .30; however, two issues with the model fit were identified. The Hosmer and Lemeshow Test was significant $p < .05$, and standardized differences between expected and observed outcomes in the Hosmer and Lemeshow Test indicated that the true *p*-value for the Hosmer and Lemeshow Test was lower than the calculated, already-significant statistic. No model was identified as fitting the data, justifying a failure to reject the null hypothesis of Research Question 2.

Chapter 5

Findings, Implications, and Conclusion

This chapter begins with a review of the purpose of the study and its research questions, followed by a review of the methodology and data analysis. A discussion of findings is then presented along with a discussion of the findings through the lens of the theoretical framework. Implications are considered, including implications for practice, policy, and future research. Finally, a conclusion and a personal reflection are presented.

Purpose of the Study

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate in online credit recovery—both those who were eligible for participation and those who were never eligible. Student factors considered in this study were gender, race and ethnicity, status as an English learner (EL), status as a student with a disability (SWD), status as economically disadvantaged, status as homeless, student's high school, and student's graduation cohort.

Research Questions

Guided by the following research questions, this study examined student participation in and graduation-rate outcomes of online credit recovery in a large school division in Virginia:

1. What were factors that explained student participation in online credit recovery?
2. How much more or less likely were students who participated in online credit recovery to graduate high school on time compared to (a) the likelihood of those

who were eligible for, but did not participate in, online credit recovery and (b) the likelihood of those who were never eligible for online credit recovery?

Review of Methodology and Analysis

This was a quantitative, *ex post facto*, and non-experimental study that created logistic regression models designed for inference testing. The setting was a large school division in Virginia, and the sampling frame was members of Graduation Cohorts 2019 and 2020 from that division. Data were collected from the division, including student factors of gender, race and ethnicity, school, status as EL, status as SWD, status as homeless, and 4-year Virginia Department of Education (VDOE) exit/withdraw code. Data were cleaned, and variables for on-time graduation, eligibility for online credit recovery, participation in online credit recovery, and grade point average were calculated.

Binary logistic regression models were developed using a framework set by Hosmer et al. (2013). Preliminary final models were created as the best logistic regression model for the dependent variables, and fit was checked for each model. The preliminary final model for both Research Questions 1 and 2 both had issues with goodness of fit statistics, and both were rejected as fitting the data. Without a valid model for Research Question 1, no student factor was able to be identified as having explaining participation in online credit recovery. Similarly, for Research Question 2, participants of online credit recovery were not found to have been any more or less likely to graduate on time compared to those who did not participate.

Discussion of the Findings

While issues with the goodness of fit for both models prevented further examination of student factors that explained participation in online credit recovery and the resulting likelihood of on-time graduation, the analysis provided four findings. This section outlines each finding, its

supporting data from Chapter 4, and its relationship with existing literature discussed in Chapter 2.

Finding 1

No student factor was found to have explained participation in online credit recovery. Research Question 1 examined student factors that may have explained participation in online credit recovery. Of the 10,010 students in the sample, only 2.3% of the students participated in online credit recovery (see Table 8), and no school accounted for more than 13.5% of division participants (see Table 9). Within each student factor, for both participants and non-participants, no group proportion was more than 10 percentage points from that factor's overall proportion of the sample (see Table 8). Finally, only one binary logistic regression model was found to have a not significant Hosmer and Lemeshow Test, and an additional test indicated that the Hosmer and Lemeshow Test may have indeed been significant (see Table 12). Consequently, no student factor was able to be identified as explaining participation in online credit recovery in School Division A.

Viano (2021), on the other hand, identified student factors that explained participation in online credit recovery. Viano reported that Black students were more likely than White students to participate in online credit recovery; however, other races and ethnicities were found to be less likely than White students to participate. Furthermore, Viano found SWD and EL students to be less likely to participate than their peers. Heinrich et al. (2019) found that participation in online credit recovery varied widely among schools, attributable to actions of school leadership.

Similar to the students in School Division A, Hart et al. (2019) found that the participants in online credit recovery in Florida were a diverse group of students. Furthermore, Hart et al. noted that "we know little about the generally-unobservable factors that motivate online

enrollment in high school" (p. 15). Similarly, student factors identified by Heinrich et al. (2019) that were most strongly associated with online credit recovery—student pregnancy, student parenting a child, student returning to the classroom from incarceration or expulsion, and students with high absences and low reading levels—were beyond the scope of this study.

Heinrich et al. (2019) cautioned that the systemic enrollment of one group of students in online credit recovery could "represent within-school segregation that appears to cut off some of the most academically and economically disadvantaged students from access to better quality instruction and learning opportunities" (p. 2183). The lack of finding such a student factor in School Division A may have indicated that potentially poor educational experiences were not systemically consolidated into one or more student groups (see also Heinrich et al., 2019).

Finding 2

A student's on-time graduation was neither more nor less likely given their eligibility for or participation in online credit recovery. Research Question 2 examined how more or less likely students who participated in online credit recovery graduated on time when compared to those who did not participate – both those who were never eligible and those who were eligible, but did participate. A regression model was created with a dependent variable of on-time graduate, independent variable of participation group, and covariates of student factors. The preliminary final model also included five interaction variables. The preliminary final model was rejected because it had a significant Hosmer and Lemeshow Test (see Table 20), and an additional test provided more information that the Hosmer and Lemeshow Test was likely significant (see Table 22). Consequently, it was not possible to determine if a student's participation group—never eligible, eligible but did not participate, or participated—made a student more or less likely to graduate on time than a student in a different participation group.

Both Heinrich and Darling-Aduana (2021) and Viano and Henry (2023) found that participants in online credit recovery tended to graduate on time at rates higher than their similar peers (i.e., those who were eligible but did not participate). Heinrich and Darling-Aduana calculated the rate to be 10–12 percentage points higher for participants compared to similar peers. Furthermore, Heinrich and Darling-Aduana found that those who did not participate as a whole graduated on time at a rate 3 percentage points higher than those who participated. Rickles et al. (2018) also found a significant difference between the on-time graduation rates of those not eligible for online credit recovery in Algebra 1 and those who were eligible, regardless whether the student participated online or face-to-face.

Rickles et al. (2018), however, failed to find a difference in on-time graduation rates between those who participated in online credit recovery in Algebra 1 and those who participated in face-to-face credit recovery in Algebra 1 (whose participation group would have been identified as *eligible but did not participate* in this study). Rickles et al. attributed the lack of a difference to the fact that "it may be unrealistic to expect a single credit recovery course, whether online or [face-to-face], to put failing students back on the path to on-time graduation" (p. 489). Rickles et al. also noted that the lack of a difference in graduation rates between the two groups meant that a district had flexibility in deciding how to help students recover a failed course

Finding 3

The rate of participation in online credit recovery was low compared to existing studies. Only 2.3% of the sample participated in online credit recovery despite 27% of the sample having been eligible to participate. This is equivalent to 8.5% of those eligible ultimately participating in at least one online recovery course (see Tables 8 and 9). Prior studies by Viano (2021) and Heinrich et al. (2019) found that participation in online credit recovery was nearly 10

times as common in their districts of study. From 2013–2017 in North Carolina, approximately 20% of failures in required, core courses were addressed by online credit recovery, and larger schools were more likely to have more participants in online credit recovery (Viano, 2021). Heinrich et al. found that the large urban district averaged 23.4% participation from 2014–2017.

Finding 4

Schools with higher on-time graduation rates were not necessarily associated with online credit recovery, and participation was relatively uniformly distributed. The two schools with the highest on-time graduation rates (OTGR), School 2 (99.5%) and School 8 (98.8%), accounted for the fewest participants in online credit recovery, 7.4% of participants combined (see Tables 7 and 9). As no single school accounted for more than 13.5% of the participants, participation was relatively uniformly distributed among the schools. The five schools that had the most participants in online credit recovery—Schools 10, 3, 5, 4, and 1, listed in order of participants from most to fewest—accounted for 62.6% of the participants. School 10 had the fourth-highest OTGR at 95.2%. School 3 had the eighth-highest OTGR at 92.4%. School 5 had the seventh-highest OTGR at 94.0%. School 4 had the ninth-highest OTGR at 90.7%. School 1 had the third-highest OTGR at 97.2%. In contrast, Viano (2021) found that schools with higher graduation rates were associated with higher rates of participation in online credit recovery. This finding does support the findings of Heinrich et al. (2019)—variance among schools in number of students participating in online credit recovery was related to decisions made by school-level administrators and leaders and to recommendations from and practices set by district leaders.

Discussion of Findings and the Theoretical Framework

This study was based on the theoretical perspectives of *new institutionalism* in education (Meyer & Rowan, 2006). Meyer and Rowan (2006) highlighted that "established institutions [e.g., schools, districts, etc.] become more market minded and entrepreneurial" (p. 2) in response to increased control of schools through federal and state accountability measures. Rowan (2006) also indicated that there has been support for the idea that educational institutions tend to grow isomorphically—developing into a similar structure to others through natural processes, processes designed to mimic the structure of others, or coercive processes. A recurrent problem identified in educational institutions is low on-time graduation rates of certain groups of students (Atwell et al., 2019; Elbaum et al., 2014; McFarland et al., 2020; Murnane, 2013; Smith et al., 2012; Stark & Noel, 2015; Sublett & Chang, 2019). In response, businesses and economic markets, such as those promoting online credit recovery, have influenced change in K-12 schools in the United States in an attempt to solve the recurrent problem (Rowan, 2006; Mullen, 2022).

Finding 3 contradicted the findings of multiple studies that suggested that online credit recovery was becoming increasingly popular and pervasive in schools (Hart et al., 2019; Heinrich et al., 2019; Viano, 2021; Viano & Henry, 2023). Because School Division A was presented with the same pressure of increased control by federal and state accountability measures, new institutionalism would have predicted that School Division A would have grown isomorphically with its fellow institutions. While School Division A did grow isomorphically by offering online credit recovery, the smaller proportion of students participating in School Division A was a departure from the expected isomorphic change in practice under this theoretical framework based on existing literature about other districts.

Of the possible explanations for this departure from the framework, there are two that are related to this study and its connection to the other studies referenced. First, School Division A is a suburban school division, and the settings of the referenced studies were either urban districts or entire states that included all urban, suburban, and rural districts. Second, the setting for this study was Virginia, different from the settings of any of the referenced studies, thus highlighting the lack of generalizability noted by the researchers in the referenced studies.

Implications

Implications for Practice

Based on the four findings, three implications for practice emerged.

Implication 1: School and district leaders should continue to examine patterns of student participation in online credit recovery. Finding 1 indicated that no student factor was found to have explained participation in online credit recovery; however, this is not conclusive evidence that no student factor explained participation. Hart et al. (2019) indicated that there are "generally-unobservable factors" (p. 15) that are associated with online credit recovery, and Heinrich et al. (2019) found risk factors existed that were associated with online credit recovery participation. These risk factors, such as a pregnant student or a student returning from incarceration or expulsion, were beyond the scope of the study. School and district leaders should consider that students may be systemically participating in online credit recovery based on a student factor, diverting away from quality learning experiences and instructors (Heinrich et al., 2019). Continued examination of patterns may help to highlight any systemic participation. This implication is related to Findings 1 and 3.

Implication 2: School and district leaders should utilize the flexibility in choosing online credit recovery with other credit recovery options given similar on-time graduation

outcomes. The study did not find a significant likelihood of on-time graduation dependent on a student's eligibility for or participation in online credit recovery. This finding is similar to that of Rickles et al. (2018) where there was no significant difference in rates of on-time graduation of participants in online credit recovery in Algebra 1 or participants in face-to-face credit recovery in Algebra 1. The lack of a significant difference means that school and district leaders have flexibility in selecting methods for helping students recover credits given participation in online credit recovery did not increase or decrease a student's likelihood of graduating on time. Considering the varied participation rate of each school as identified in Finding 4, this flexibility may already be in use by school and district leaders in School Division A. This implication is related to Findings 2 and 4.

Implication 3: School and district leaders should consider reevaluation of selection criteria for student participation in online credit recovery. Finding 3 indicated that only 8.5% of those eligible for online credit recovery ultimately participated in at least one online credit recovery course. As noted by Heinrich et al. (2019), participation in online credit recovery has been found to be related to decisions made by school-based administrators and leaders. School leaders may also make these decisions based on recommendations from or practices set by district-level leaders (Heinrich et al., 2019). School and district leaders may consider reevaluating how students are selected for online credit recovery to ensure that selection criteria are consistent with finding the best option for each student (Viano, 2021). This implication is related to Findings 1 and 3.

Implications for Policy

Based on the four findings, one implication for policy emerged.

Implication 4: State education agencies should publicly report frequency and summary statistics about students who participated in online credit recovery. Finding 1 failed to find student factors that explained participation in online credit recovery, and Finding 2 failed to find associations between the likelihood of on-time graduation and participation group. Data are not currently available publicly in all states, and researchers interested in studying online credit recovery must gain approval and cooperation from individual districts to collect that data. Data about online credit recovery are not publicly available in Virginia, and the attempt by the researcher to collect data on online credit recovery participation and on-time graduation outcomes from three school divisions resulted in only one both agreeing to participate and providing data.

Some states, like North Carolina and Florida, have publicly available data that can be used by researchers to draw conclusions across multiple districts and regions in the state (Hart et al., 2019; Viano, 2021). Given some of the potential negative implications that come with participation in online credit recovery (Heinrich and Cheng 2022; Heinrich et al., 2019; Powell, Roberts, et al., 2015), state agencies should consider publicly reporting frequency and summary statistics about students who participated in online credit recovery to include student factors normally collected and published by the agency (Tyner & Munyan-Penney, 2018). This implication is related to Findings 1, 2, and 3.

Implications for Future Research

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate

in online credit recovery—both those who were eligible for participation and those who were never eligible. The findings of this study may offer opportunities for further inquiry and research into how schools and districts provide online credit recovery to students.

Future studies may consider adding a qualitative component to this study in the same setting or different setting. This may include examining the opinions and decisions of school-based and district-based leaders as identified by Heinrich et al. (2019) or examining student participants qualitatively to find the "generally-unobservable factors that motivate online enrollment in high school" (Hart et al., 2019, p. 15). A future study may also consider investigating why and how school divisions select multidivision online providers.

Expanding the setting beyond one school division is another opportunity for future research. Focusing on understanding participation and on-time graduation in divisions of different sizes or locations, including urban, rural, and suburban division, may help to provide clarity for the discrepancies in literature highlighted by the four findings of this study. A future study may also replicate this study for different graduation cohorts. Future research may expand the scope of study, investigating the performance of participants on other educational assessments (e.g., end of course assessments, national standardized testing, etc.) or the post-secondary outcomes or experiences of participants.

Conclusion

The purpose of this study was to (a) identify explanatory student factors that were associated with participation in online credit recovery by students in a large school division in Virginia and (b) compare the likelihood of on-time graduation of students who participated in online credit recovery with the likelihood of on-time graduation of those who did not participate in online credit recovery—both those who were eligible for participation and those who were

never eligible. Data was collected from the participating school division, and regression models were created. However, both models did not meet standard measures for goodness of fit and resulted in a failure to reject both null hypotheses.

While the models were unable to identify student factors that explained participation in online credit recovery or compare the likelihood of student on-time graduation based on their participation group, two additional findings were identified. First, only 2.3% of the sample participated in online credit recovery, equivalent to 8.5% of those eligible. Second, the participation was relatively uniformly distributed over all 11 high schools in School Division A, and no single school accounted for more than 15% of the participants in the sample.

Studies have highlighted benefits for students participating in online credit recovery, including higher on-time graduation rates; however, studies have also cautioned about possible negative implications for students who participate in online credit recovery. Schools and districts should continue to monitor who is participating in online credit recovery to identify if any student factors explain participation, and they should consider evaluating their selection criteria to ensure that online credit recovery is available to the appropriate students. These findings also support the schools and district in their use of flexibility in offering both online credit recovery alongside other recovery strategies. From a policy perspective, state agencies may consider making district and state data publicly available for review by those interested in how online credit recovery is being implemented in the state.

Reflection

Educational leaders have been placed in a precarious position by federal accountability—improve learning outcomes for students or face penalties. While theoretically aligned with the goals of our leaders, the practice of some has been improvement of outcome metrics by any

means necessary. This has clouded innovation in high school education, prompting questions about whether an innovation is a legitimate improvement in educating our youth or another gaming strategy. The question carries more weight when the innovation has a cost that is ultimately paid to a private contractor. Online credit recovery is one such innovation.

Starting this study, I wanted to learn more about how effective this intervention was at achieving the goal that it purports to solve—helping at-risk students stay on track to graduate on time. As a former math major and high school math teacher, I also wanted to do a study that would challenge me with new quantitative methodologies. Despite challenges and models that refused to fit data, I believe that I managed to achieve both in this study.

Given the narrative that online credit recovery is pervasive in K-12 education, I was surprised to see the participation rate in the participating division to be as low as it was. Given the inability to find a model that fit the data, I believe that this shows that online credit recovery has not become a quick fix for graduation for a certain group of students in School Division A; however, there is the distinct possibility that such a group exists for a student factor not considered in this study.

I was disappointed that I was not able to compare the findings of the participating division with that of other similar divisions. Anecdotal research of the three similar divisions that formed the initial purposive sampling frame indicated that each have taken a very different approach to online credit recovery, and studying those differences may have added to findings. I am also very appreciative of the participating school division for the data that they collected and shared, and I am curious whether the ability to consider a variable of student status as economically disadvantaged would have added to the findings.

I am hopeful that this study may encourage future research into online credit recovery in our high schools in the United States. Given the problems of generalizability of these studies, any inquiry into online credit recovery provides new information to understand this innovation and its ethical place in supporting at-risk students. In particular, I am curious what a qualitative study might find in working with the school and district leaders who make decisions about how online credit recovery is operationalized in their schools. I am also curious about what may be found if this study were replicated, either in a different setting or with different student factors.

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Appendix A

Virginia Student Exit/Withdraw Codes

Code	VDOE Exit/Withdraw Definition	Action
W016	Withdraw to enter Individualized Student Alternative Education Program (ISAEP) - A student who withdraws from school and enrolls in a GED preparation program as a part of an ISAEP as defined in Code of Virginia § 22.1-254.D and Board of Education guidelines. A student in an ISAEP will maintain this withdraw code until he or she exits the program. A student in an ISAEP shall be counted in the membership and average daily membership (ADM) of the local education agency.	Include in sample as non-graduate
W115	Transfer to another room in the same school - A student who transfers to another room within the same school.	Include in sample as non-graduate
W118	Transfer to a special education program from regular education program within the school - A student who transfers to a special education program within the same school from a regular education program during the school year.	Include in sample as non-graduate
W119	Transfer to regular education program from special education program within the same school - A student who transfers during the school year to a regular education program from a special education program within the same school.	Include in sample as non-graduate
W201	Transfer to a public school in the same local education agency - A student who transfers to a public school that is located within the administrative boundaries of the same local education agency.	Exclude from sample
W212	Transfer to a charter school in the same local education agency - A student who transfers to a charter school, operated in accordance with state regulations, within the same local education agency.	Exclude from sample
W214	Matriculation to another school within the same local education agency - A student who enters another school after successful completion and promotion from the highest instructional level of the current school to the next higher level.	Include in sample as non-graduate
W217	Transfer to homebound instruction - A student who transfers to a period of homebound instruction provided by the local education agency.	Include in sample as non-graduate

Code	VDOE Exit/Withdraw Definition	Action
W218	Transfer to a special education program from regular education program that is located within the same local education agency - A student who transfers to a special education program that is located within the same local education agency.	Include in sample as non-graduate
W219	Transfer to regular education program from special education program that is located within the same local education agency - A student who transfers during the school year to a regular education program from a special education program within the same local education agency.	Include in sample as non-graduate
W221	Transfer from an Individualized Student Alternative Education Program (ISAEP) to a regular education program in a school within the same local education agency - A student who discontinues involvement in an ISAEP and transfers to a regular education program in a school within the same local education agency.	Include in sample as non-graduate
W222	Transfer to home-based instruction - A student who transfers to a period of home-based instruction provided by the local education agency.	Include in sample as non-graduate
W223	Transfer to Home-education instruction- a student who transfers to a period of Home-ed instruction provided by the local education agency.	Include in sample as non-graduate
W304	Transfer to a private, non-religiously-affiliated school in the same local education agency - A student who transfers to a private school (operated by a non-governmental, non-religious group or organization) that is located within the administrative boundaries of the same local education agency, including hospital teaching programs.	Exclude from sample
W305	Transfer to a private, non-religiously-affiliated school in a different local education agency in the same state - A student who transfers to a private school (operated by a non-governmental, non-religious group or organization) that is not located within the administrative boundaries of the same local education agency but is in the same state, including hospital teaching programs.	Exclude from sample
W306	Transfer to a private, non-religiously-affiliated school in a different state - A student who transfers to a private school (operated by a non-governmental, non-religious group or organization) that is located in another state, including hospital teaching programs.	Exclude from sample

Code	VDOE Exit/Withdraw Definition	Action
W307	Transfer to a private, religiously-affiliated school in the same local education agency - A student who transfers to a private school (affiliated with and operated by a non-governmental, religious group or organization) that is located within the administrative boundaries of the same local education agency, including hospital teaching programs.	Exclude from sample
W308	Transfer to a private, religiously-affiliated school in a different local education agency in the same state - A student who transfers to a private school (affiliated with and operated by a non-governmental, religious group or organization) that is not located within the administrative boundaries of the same local education agency but is in the same state, including hospital teaching programs.	Exclude from sample
W309	Transfer to a private, religiously-affiliated school in a different state - A student who transfers to a private school (affiliated with and operated by a non-governmental, religious group or organization) that is located in another state, including hospital teaching programs.	Exclude from sample
W310	Transfer to a school outside of the country - A student who transfers to a school outside the country that is not a United States overseas dependents school (includes private and public school systems). Students who leave the United States are not considered dropouts. Pursuant to 34 C.F.R. §200.19(b)(1)(ii)(B), a school must have written confirmation that a student has emigrated to another country, but need not obtain official written documentation.	Exclude from sample
W311	Leaves school under the authority of a US government agency – A student who leaves a Virginia Public School under the authority of a United States federal government agency. This code does not include students incarcerated in federal prison. It also does not pertain to students of military families who transfer into Department of Defense schools or who relocate due to a parent's military duty.	Exclude from sample
W312	Transfer to a charter school that is not located within the administrative boundaries of the same local education agency but is in the same state- A student who transfers to a charter school, operated in accordance with state regulations, that is not located within the administrative boundaries of the same local education agency but is in the same state.	Exclude from sample

Code	VDOE Exit/Withdraw Definition	Action
W313	Transfer to home schooling - A student who transfers to a period of instruction in a home environment for reasons other than health.	Exclude from sample
W314	Transfer to Job Corps/Virginia Commonwealth Challenge Youth Academy - A student who withdraws to enter these public educational and vocational training programs and is not concurrently enrolled in a school in the local education agency.	Include in sample as non-graduate
W321	Transfer to a full-time, baccalaureate or associate's degree seeking program at an accredited postsecondary institution - A student, who is fully prepared for postsecondary education, transfers to an accredited postsecondary institution of higher education to enter into a full time program leading to a baccalaureate or associate's degree. This code can only be used for the student who has left Virginia public schools without a credential and is enrolled full-time at an accredited postsecondary institution in a program of study that leads to a baccalaureate or an associate's degree.	Include in sample as non-graduate
W400	Summer withdrawal from the educational component of a state-operated program.	Include in sample as non-graduate
W402	Transfer to a public school in a different local education agency in the same state - A student who transfers to a public school that is not located within the administrative boundaries of the same local education agency but is in the same state. This DOES NOT include correctional institutions operated by the Department of Juvenile Justice (formerly Department of Correctional Education schools).	Exclude from sample
W411	Transfer to a state-operated juvenile detention center institution - A student who transfers to a state-operated institution that has an educational program. This ONLY includes juvenile service agencies and detention facilities.	Exclude from sample
W412	Transfer from a State Operated (SOP's) educational program to the same or different SOP with an educational program and are referred as Community Placement Program, Central Admission and Placement (CAP) and Re-Entry. For State Operated Programs use only	Exclude from sample
W415	Transfer to a state-operated hospital institution - A student who transfers to a state-operated institution that has an educational program. This ONLY includes hospital education programs, mental health institutions and care shelters.	Exclude from sample

Code	VDOE Exit/Withdraw Definition	Action
W423	Transfer into an institution operated by the Department of Juvenile Justice	Exclude from sample
W503	Transfer to a public school in a different state - A student who transfers to a public school that is located in another state, to a United States overseas dependents school, or to a Department of Defense (DOD) school.	Exclude from sample
W650	Death - A student whose membership is terminated because he or she died during or between regular school sessions.	Exclude from sample
W730	Graduated with diploma - A student who has received a standard, advanced studies, International Baccalaureate or other type of diploma upon completion of state and local requirements for both coursework and assessment.	Include in sample as a graduate
W731	Completed school with other credentials - A student who has received a GED, certificate of completion, or other credential in lieu of a high school diploma.	Include in sample as a graduate
W732	Leaves school after earning a non-terminal diploma or certificate of completion in a previous school year – A student with an IEP who returns for eligible services after completing high school in a previous school year.	Include in sample as non-graduate
W870	Discontinued schooling - A student who stops attending school because of incarceration, who is sentenced to serve time in a local, regional, or adult jail (regardless of the state or country of imprisonment) or federal prison. Do not use this code for youth adjudicated in state operated programs.	Include in sample as non-graduate
W880	Discontinued schooling - A student who stops attending school. For students in K-12, this is considered to constitute "dropping out."	Include in sample as non-graduate
W960	Withdrawn after being absent fifteen (15) consecutive days for extended illness - A student who left school for an indefinite period of time because of a physical, extended illness and is expected to return to school.	Include in sample as non-graduate
W961	Suspension exceeding 15 days - A student who left school involuntarily due to a school-approved suspension that exceeded 15 days and is expected to return to school.	Include in sample as non-graduate

Code	VDOE Exit/Withdraw Definition	Action
W970	Withdrawn after being absent fifteen (15) consecutive days - A student who has been absent for fifteen (15) consecutive days who is expected to re-enter school. At the end of the school year, a student who has not returned to school should be recoded to the appropriate exit/withdraw type.	Include in sample as non-graduate

Note. Adapted from "Student Record Collection Code Values: Exit/Withdraw Codes" by the Virginia Department of Education, n.d.-g, retrieved September 1, 2023 from https://www.doe.virginia.gov/data-policy-funding/data-reports/data-collection/student-record-collection/student-records-code-values.

Appendix B

Multidivision Online Providers in Virginia, 2023-2024

Program	Participating Divisions	Online Credit Recovery Offered
ACCEL Online East	0	No
Accelerate Education	1	Yes
Apex Learning	28	Yes
BYU Independent Study	4	Yes
Chesterfield County Public Schools – CCPSOnline	9	No
Connections Education LLC dba Pearson Virtual Schools	1	No
EdisonLearning, Inc	2	Yes
Edmentum EdOptions Academy	33	Yes
Florida Virtual School: FlexPoint	3	Yes
Founders Education	16	Yes
Greenways Academy	0	No
Hampton City FLEx	0	No
Imagine Edgenuity	58	Yes
Imagine Learning LLC / OdysseyWare Academy	1	Yes
Middleton Academy	0	Yes
My Virtual Academy	0	Yes
Nextide Academy	0	No
Proximity Learning, Inc	11	No
RISE Hybrid Private Academy	0	No

Program	Participating Divisions	Online Credit Recovery Offered
SchoolsPLP, LLC	0	Yes
Stride K12	26	No
Stride Learning Solutions	5	Yes
The Coding School	1	No
VHS Learning	1	No

Note. Adapted from "Approved Multidivision Online Providers List" by the Virginia Department of Education (n.d.-a), retrieved September 25, 2023, from https://p1pe.doe.virginia.gov/amop_public/.

Appendix C

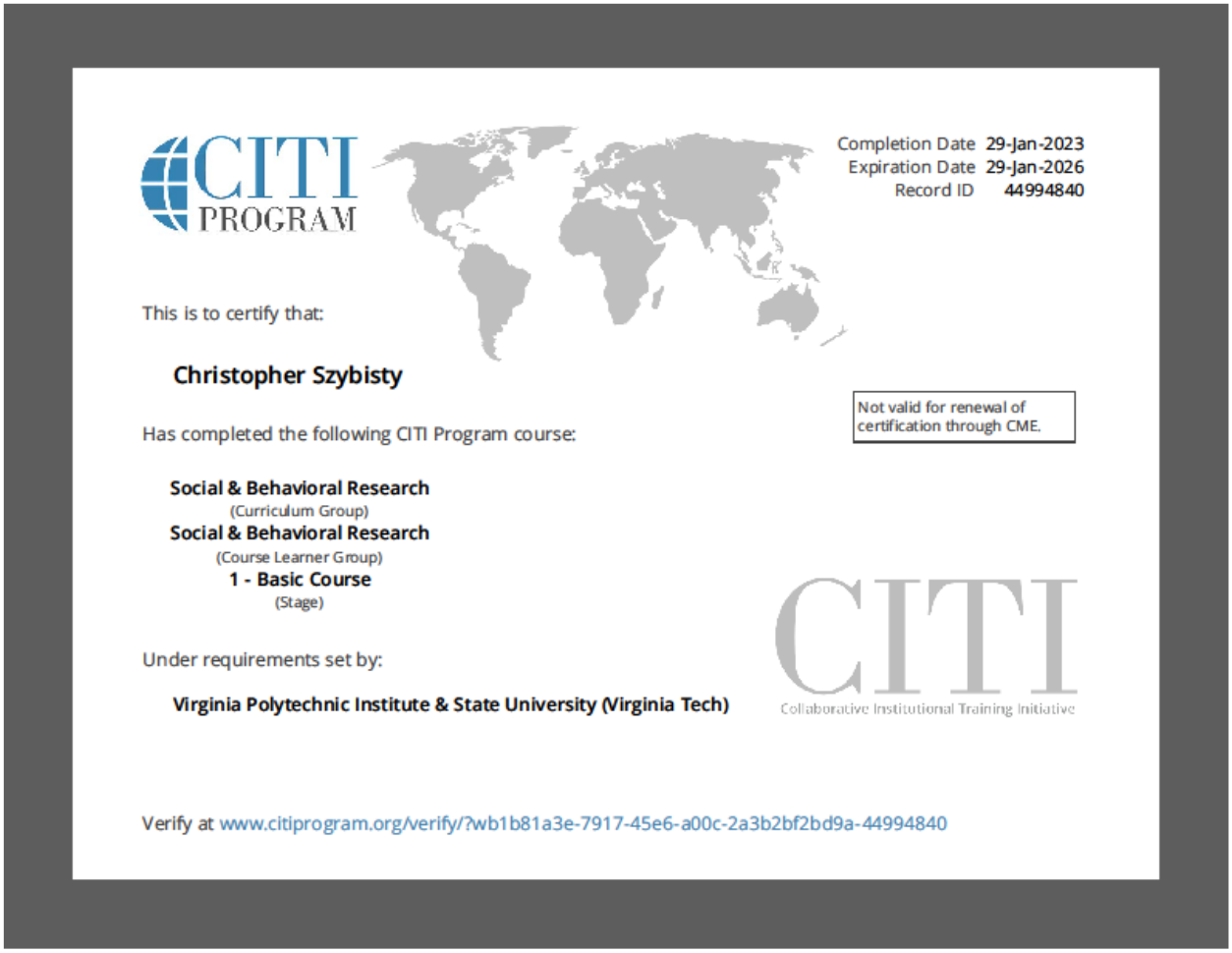
Large School Divisions in Virginia

Division	Region	Total Enrollment	
		2019	2020
Arlington County	Northern	27,434	28,151
Chesapeake City	Hampton Roads	40,898	41,597
Chesterfield County	Central	61,608	62,669
Fairfax County	Northern	187,830	188,930
Henrico County	Central	51,523	51,786
Loudon County	Northern	82,238	83,933
Newport News City	Hampton Roads	28,654	28,655
Norfolk City	Hampton Roads	30,087	29,837
Prince William County	Northern	90,876	92,270
Richmond City	Central	24,763	25,212
Stafford County	Northern	29,485	30,120
Virginia Beach City	Hampton Roads	68,624	68,706

Note. Adapted from "Fall membership build-a-table" by the Virginia Department of Education (n.d.-d), retrieved September 12, 2023, from https://p1pe.doe.virginia.gov/apex_captcha/home.do?apexTypeId=304, and adapted from "Virginia Regional Map" by the University of Virginia (2017).

Appendix D

Social and Behavioral Research Training Certificate



CITI PROGRAM

Completion Date 29-Jan-2023
Expiration Date 29-Jan-2026
Record ID 44994840

This is to certify that:

Christopher Szybisty

Not valid for renewal of certification through CME.

Has completed the following CITI Program course:

Social & Behavioral Research
(Curriculum Group)
Social & Behavioral Research
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

Virginia Polytechnic Institute & State University (Virginia Tech)

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wb1b81a3e-7917-45e6-a00c-2a3b2bf2bd9a-44994840

Appendix E

IRB Exemption

Division of Scholarly Integrity and
Research Compliance
Institutional Review Board
North End Center, Suite 4120 (MC 0497)
300 Turner Street NW
Blacksburg, Virginia 24061
540/231-3732
irb@vt.edu
http://www.research.vt.edu/sirc/hrpp

VIRGINIA TECH

MEMORANDUM

DATE:	October 31, 2023
TO:	Charles L Lowery, Christopher Conrad Szybisty
FROM:	Virginia Tech Institutional Review Board (FWA00000572)
PROTOCOL TITLE:	Online Credit Recovery and On-Time Graduation in Large Virginia School Divisions
IRB NUMBER:	**23-1134**

Effective October 31, 2023, the Virginia Tech Human Research Protection Program (HRPP) determined that this protocol meets the criteria for exemption from IRB review under 45 CFR 46.104 (d) category(ies) 4(ii).

Ongoing IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities impact the exempt determination, please submit an amendment to the HRPP for a determination.

This exempt determination does not apply to any collaborating institution(s). The Virginia Tech HRPP and IRB cannot provide an exemption that overrides the jurisdiction of a local IRB or other institutional mechanism for determining exemptions.

All investigators (listed above) are required to comply with the researcher requirements outlined at:

https://secure.research.vt.edu/external/irb/responsibilities.htm

(Please review responsibilities before beginning your research.)

PROTOCOL INFORMATION:

Determined As:	**Exempt, under 45 CFR 46.104(d) category(ies) 4(ii)**
Protocol Determination Date:	**October 31, 2023**

ASSOCIATED FUNDING:

The table on the following page indicates whether grant proposals are related to this protocol, and which of the listed proposals, if any, have been compared to this protocol, if required.

Appendix F

Variables for Analysis in the Study

Name	Type	Description	Values	IV/EV/DV	RQ
ID	Nominal	De-identified student ID	Unique code (e.g., ABC1234567)	N/A	N/A
Gender	Nominal	Student gender	0: Female [a] 1: Male 2: Other [c]	EV	RQ1, RQ2
Race and Ethnicity	Nominal	Student resolved race and ethnicity	0: American Indian or Alaska Native 1: Asian 2: Black or African American 3: Hispanic 4: Native Hawaiian or Other Pacific Islander 5: Two or more races 6: Unknown race [c] 7: White [a]	EV	RQ1, RQ2
EL	Nominal	Student status as an English learner	0: Not EL 1: EL	EV	RQ1, RQ2
SWD	Nominal	Student status as a student with a disability	0: Not SWD 1: SWD	EV	RQ1, RQ2

Name	Type	Description	Values	IV/EV/DV	RQ
EconDA [b]	Nominal	Student status as economically disadvantaged	0: Not Economically Disadvantaged 1: Economically Disadvantaged	EV	RQ1, RQ2
Homeless	Nominal	Student status as homeless	0: Not Homeless 1: Homeless	EV	RQ1, RQ2
Graduation	Nominal	Classification as on-time graduate	0: Did not graduate on time 1: Graduated on time	DV	RQ 2
Cohort	Nominal	Identifies a student's cohort year	0: 2019 1: 2020	EV	RQ1, RQ2
School	Nominal	Identifies the school to which the student was assigned	0: School 0 [a] 1: School 1 . . . 10: School 10	EV	RQ1, RQ2
GPA	Continuous	Student Grade Point Average of High School Courses	Integer between 0.00 and 4.00, inclusive, rounded to two decimal places	EV	RQ1, RQ2

Name	Type	Description	Values	IV/EV/DV	RQ
Eligible	Nominal	Classification for eligibility for online credit recovery	0: Was not eligible for participation in online credit recovery 1: Was eligible for participation in online credit recovery	N/A	N/A
Participated	Nominal	Classification for participation in online credit recovery	0: Did not participate in Online Credit Recovery 1: Participated in Online Credit Recovery	DV	RQ1
PartGroup	Nominal	Classification of student's participation group	0: Never eligible for online credit recovery 1: Eligible for but did not participate in online credit recovery 2: Participated in online credit recovery [a]	IV	RQ 2

[a] Group is selected as the reference group for the polytomous variable.

[b] School Division A did not provide data on student status as economically disadvantaged.

[c] Category did not have any students in the sample and was eliminated as a part of data cleaning.