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The Impact of Freshmen On-Track Status, Absenteeism, and Associated Demographic Variables on Four-Year Graduation Attainment within a Rural Community: A Predictive Validity Study

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"THE IMPACT OF FRESHMEN ON-TRACK STATUS, ABSENTEEISM, AND ASSOCIATED DEMOGRAPHIC VARIABLES ON FOUR-YEAR GRADUATION ATTAINMENT WITHIN A RURAL COMMUNITY: A PREDICTIVE VALIDITY STUDY," a Doctoral research project prepared by JOEL HOFF in partial fulfillment of the requirements for the Doctor of Education degree in Educational Leadership.

This dissertation has been approved and accepted by:

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Abstract

This study analyzed the predictive validity of key dropout indicators at the freshmen year within a rural school district. Specifically, the study examined the predictive validity of the freshmen on-track indicator and freshmen absenteeism as predictors of four year, on-time graduation attainment. While most of the Early Warning System (EWS) research has taken place in large urban and suburban schools districts, this study used secondary data spanning four years from a small, rural school district. Additionally, the study sought to explore which student academic and behavior metrics had the greatest predictive validity for the rural student sample. Binomial logistic regression was used to analyze the secondary data. The analysis found a statistically significant relationship between graduation attainment and three of the study's variables (economically disadvantaged status, freshmen on-track status, and absenteeism). Developing effective dropout prediction models can assist educators in providing more timely and targeted interventions for potentially at-risk students. Additionally, the results of this study may provide additional insights into the predictive capabilities of these key student academic and behavioral early warning indicators with rural student samples.

Key words: Freshmen On-Track, Dropout Prediction, Early Warning Indicators, Rural Schools

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Chapter One

At 2:46 pm on March 11th, 2011, Japan's earthquake Early Warning Alert System sent out an alert ringing across the country. Seismographs detected deep seismic activity, signaling an imminent large-scale earthquake. As residents scrambled for cover and began feeling the earth shake beneath them, a second alert, this time from the Tsunami Early Warning Alert System, echoed across the island sending people running for high ground. Nine minutes later, one of the largest tsunamis in modern history ravaged the Japanese coastline (Talbot, 2011). Once the damage was done, 15,896 people had died as a result of the natural disaster (National Police Agency of Japan, 2018). Although the loss of life was tremendous, the additional warning time provided by the earthquake and tsunami early warning alert system potentially saved hundreds of thousands of lives (Talbot, 2011). The Great Kanto Earthquake of 1923, a similar natural disaster, killed an estimated 142,000 people (James, 2002). The additional time provided by Japan's early warning systems was instrumental in saving thousands of lives.

Just as Japan's early warning alert systems helped to provide warning of an imminent natural disaster, the educational field has adopted its own type of early warning system (EWS) to detect when a student may be at-risk of dropping out. Educational EWS offer school leaders the ability to identify potential dropouts earlier in a student's academic career in order to offer additional academic and social support. These systems rely on multiple longitudinal student variables to identify students who have a higher likelihood of dropping out if no additional support is provided (Balfanz, Herzog, & Mac Iver, 2007; Bowers, 2010). The use of EWS have grown rapidly in popularity and precision since first appearing in the 1970s (Bowers, 2010; Bruce, Bridgeland, Balfanz, & Horning Fox, 2011; Lloyd, 1978; Pinkus, 2008). While the implementation of EWS has increased, there is yet to be a conclusive set of established student

variables that are consistently used in all EWS (Franklin & Trouard, 2016; Gleason & Dynarski, 2002; Stuit et al., 2016). Without a clear consensus regarding the most predictive early warning indicators, it is important to analyze the context and predictive validity of the vast array of student variables that have been used by educational researchers in order to gain further clarity on which variables will be the most effective predictors for on-time graduation attainment.

Rationale of the Study

The impact of dropping out of school has far-reaching economic and social consequences for both the individual student as well as their local community (Kennelly & Monrad, 2007; Rumberger, 2011). Since the mid-20th century, educational leaders have sought to provide more effective educational practices in order to prevent students from dropping out (Dorn, 2003). Despite improvement in raising our nation’s graduation rates, one in five students still failed to graduate with a regular high school diploma within four years of entering high school in the United States (McFarland, Cui, & Stark, 2018). The necessity to solve our nation’s dropout problem has led to a number of local and national dropout intervention practices, chief among them being the EWS.

EWS have emerged as a powerful and effective dropout prevention tool. Analyzing student academic, behavioral, and demographic variables to identify potential dropouts can have a dramatic impact on a school district’s ability to support at-risk students (Bruce et al., 2011). Early identification of at-risk students allows school districts to provide timelier academic and social supports for at-risk students while there is still adequate time to intervene. Furthermore, using early warning indicators with high accuracy and predictive validity can help channel the limited resources of school districts to the students who are in most need of support (Balfanz & Legters, 2010). Unfortunately, no early warning indicator has proven to be entirely accurate

(Bowers, Sprott, & Taff, 2013; Bruce et al., 2011; Gleason & Dynarski, 2002) and using early warning indicators that fail to identify at-risk students or misidentify students who are not in jeopardy of dropping out can have negative consequences for both students and school districts.

While the potential impact of EWS is clear, researchers have not reached a consensus on determining which student variables are most effective at identifying potential dropouts. Studies from across the world have examined the predictive validity of a wide array of student variables ranging from 3rd grade reading scores (Hernandez, 2011) to maternal graduation status (Ensminger & Slusarcick, 1992a) to the number of cigarette packs smoked per week (Mensch & Kandel, 2018). As Johnson and Semmelroth (2010) explain, "…differences in the local context may dictate different predictors, different cut scores, or different approaches to screening" (p. 123). From the vast collection of student variables analyzed for their correlation to graduation attainment, only a small number of early warning indicators have emerged as strong starting points for developing an effective EWS.

Although there is not an overall consensus, the ABCs (attendance, behavior, course performance) of EWS developed by Balfanz, Herzog, and Mac Iver (2007) are the preeminent set of variables for identifying at-risk students (Balfanz et al., 2007). Yet further research was needed to determine whether the same predictive validity exists with these variables among different student populations and geographic locations than observed in the initial research (Johnson & Semmelroth, 2010).

Purpose of Study

While a number of studies indicated higher graduation rates dependent on gender (Burke, 2015; Dalton, Glennie, & Ingels, 2009; Roderick, 1993; Soland, 2013; Uekawa, Merola, Fernandez, & Porowski, 2010), race/ethnicity (Burke, 2015; Hess, Alfred, & Lauber, 1985; Neild

& Balfanz, 2006; Uekawa et al., 2010), socioeconomic status (Dalton et al., 2009; Ensminger & Slusarcick, 1992b; Franklin & Trouard, 2016; Hernandez, 2011; Paasch & Swaim, 1993; Saunders, Silver, & Zarate, 2008; Suh, Suh, & Houston, 2007), SPED identification (Balfanz et al., 2007; Burke, 2015; Uekawa et al., 2010), and English as a second language identification (Allensworth & Easton, 2012; Balfanz et al., 2007; Saunders et al., 2008), the purpose of this study was to investigate and analyze the extent to which high school freshmen credit attainment and freshmen absenteeism were early warning indicators of four-year graduation attainment within a rural, Oregon school district. These two student variables have shown high predictive validity for identifying potential dropouts in a number of studies that have taken place primarily with large, urban student populations (Allensworth, 2013; Allensworth & Easton, 2007; Bowers, 2010; Mac Iver & Messel, 2013; Neild, Balfanz, & Herzog, 2007). The study's sample came from the Kentwood School District (pseudonym) located in a rural county of Oregon. The school district was comprised of roughly 3,000 students of which 76% were white, 16% were Hispanic/Latino, 6% were Multiracial, and a small remaining percentage were classified as other race/ethnicities. Additionally, 61% of the students received free or reduced lunch, 14% received special education services, and 9% of the students were Ever English Learners.

Based on the research literature, a student's academic performance from their freshmen year may be considered the most pivotal in determining whether or not that student will graduate (Allensworth, 2013; Heppen & Therriault, 2008; Herlihy, 2007). Although selecting student variables from earlier in a student's academic career would allow for more time for intervention, those indicators tend to have lower predictive validity (Bowers et al., 2013). Correctly identifying the most at-risk students at the end of their freshmen year allows educators three years of intervention time before a student is projected to graduate. Furthermore, since Oregon

school districts are already required to report their freshmen on-track and chronic absenteeism information to the Oregon Department of Education (ODE), data for these two variables is easily accessible for educators. Utilizing early warning indicators for which the student data is readily available to educators allows for a more seamless EWS implementation because it does not require labor-intensive data collection techniques such as student surveys or teacher interviews (Davis, Herzog, & Legters, 2013). This study, therefore, sought to explore the predictive validity of two independent variables and five demographic covariates that are readily available for Oregon school districts.

Research Questions

1) To what extent did the freshmen on-track indicator status predict the probability that a student graduated within four years?
2) To what extent did the total number of days a student was absent their freshmen year predict the probability that the student graduated within four years?
3) To what extent did combining a student's freshmen on-track indicator status and total number of days absent their freshmen year, predict the probability that the student graduated within four years?
4) To what extent did the freshmen on track indicator status, total number of days a student was absent their freshmen year, and demographic variables (gender, race/ethnicity, SPED, LEP, and SES) predict the probability of four-year graduation attainment?

Significance of Study

Developing effective dropout identification and intervention practices has several practical applications. First and foremost, developing an effective EWS has shown promise in

reducing the number of high school dropouts by providing school districts with early identification of at-risk students (Allensworth & Easton, 2007; Jerald, 2006; Mac Iver & Messel, 2013). School districts that successfully implement EWS and corresponding student support systems may reduce their dropout rates and therefore provide positive economic and social benefits to their local communities (Rumberger, 2011). On a local level, the results of this study have potential to increase the Kentwood School District's ability to use specific student variables to predict the likelihood that a student may become a non-graduate. This may allow the district to provide more focused interventions for at-risk students and in turn, may lead to an increase in the number of students graduating each year. Additionally, if the freshmen on-track indicator and absenteeism demonstrate high predictive validity for graduation attainment, this information could assist the district in allocating additional resources to help support students succeed in these two key areas.

While this study has the potential to assist the Kentwood School District in better supporting students through flagging potential at-risk students, a great deal of precaution and care must be taken in regards to the interpretations and actions that are based on EWS data. Although a powerful tool for flagging students who may be at-risk of dropping out, EWS are not without error and have the potential to misidentify students as either false positives or false negatives for dropping out. This issue provides both social and ethical considerations for the educational practitioners within the Kentwood School District.

When a student is flagged by an EWS as a potential dropout, it is essential to have several social and ethical safeguards in place to ensure that the designation does not become a self-fulling prophecy for students who are flagged. Educational research is clear that a student's self-concept and perception has both direct and indirect effects on academic achievement and

performance (Marsh & Martin, 2011; Valentine, DuBois, & Cooper, 2004). The negative impacts of insensitively or improperly labeling a student as a "potential dropout" cannot be understated. Teachers and administrators must resist using EWS identification of students as an excuse to confirm their biases or prematurely label a student as a failure. Research has demonstrated that teachers' beliefs and expectations about their students can influence their interactions with those students and therefore may lead to a self-fulfilling prophecy cycle (Brophy, 1982; Jussim & Harber, 2005). Dee Norman Lloyd, whose 1978 study was one of the earliest attempts to identify early warning indicators at the third grade level, cautioned that, "…the possible adverse effects from labeling students as "potential failures" should not be underestimated (Lloyd, 1978, p. 119)."

With this in mind, it is essential that educational practitioners view EWS identification as simply an indication to provide a student with additional academic, social, or emotional support, not an absolute label that a student is a failure who will not graduate. If communicated or handled improperly, rather than serving as a signal for educators to offer students with timely and targeted intervention, the EWS identification could have a damaging effect on the students in most need of support. Since EWS identification can modulate based on the frequency of data uploads, and has the potential for identification errors, it is crucial for the stakeholders in the Kentwood School District to view the identification as simply one data point indicating that a student may be in need of additional support.

In regards to scholarly significance, this particular study adds to the current body of research regarding the predictive validity of specific early warning indicators within a rural school setting. The vast majority of EWS research has been conducted in large, urban school districts with further research needed to focus on the value of EWS within other geographic

contexts (Gleason & Dynarski, 2002; Johnson & Semmelroth, 2010; Stuit et al., 2016). This study provides an extensive analysis of the predictive validity of specific early warning indicators for a rural student sample which may help to fill a small void within the broader field of EWS.

Definitions of Terms

Early Warning System (EWS): A collection of student measures used by educators to identify students at-risk of dropping out (Bruce et al., 2011).

Early Warning Indicators: A student variable that has demonstrated predictive ability as to whether or not a student has a higher or lower likelihood to drop out of school (Soland, 2013).

Freshmen On-Track Indicator: There exist a tremendous amount of variability in the way in which researchers have defined a freshman as being "on-track" or "off-track." Since the data source for this study was the ODE, the definition of "freshmen on-track" matched that of the ODE. For a regular Oregon high school diploma, a student must earn 24 total credits over the course of their four years in high school. As a result, a student who had earned at least six credits by the start of their sophomore year was considered a "freshmen on-track" (Oregon Department of Education, 2017).

Four-Year High School Graduate: This designation was assigned to a student who was awarded an Oregon regular high school diploma, modified diploma, extended diploma, or post-graduate scholar program within four years and one summer of beginning high school (Oregon Department of Education, 2015).

Non-Graduate: This designation applied to a student who did not receive a regular high school diploma, modified diploma, extended diploma; or, who did not participate in the post-graduate

scholar program within four years and one summer of beginning high school (Oregon Department of Education, 2015)

Dropout: This term has taken on a wide variety of definitions (Bowers et al., 2013). For this particular study, there was a subtle difference between a “non-graduate” and a “dropout.” A dropout was a student who did not receive a GED, a regular high school diploma, modified diploma, extended diploma; or, who did not participate in the post graduate scholar program, *and* was no longer enrolled in school (Oregon Department of Education, 2015).

Chronically Absent – A student who was absent more than 10% of the total enrolled school days in a school year (Oregon Department of Education, 2015).

Limitations

The major limitations of this study primarily related to the sample. Although this study examined four different cohorts of students over the course of four years, all the students were from a single district. The Kentwood school district’s 2017-2018 student population consisted of nearly 3,000 students. Of those students, 76% were White, 16% were Hispanic/Latino, 6% were Multiracial, and a fractional remaining percentage of other race/ethnicities. Additionally, 61% of the students received free or reduced lunch, 14% received special education services, and 9% of the students were Ever English Learners. Due to the specificity of the sample, the generalizability of the study’s results to other school districts with differing geographic and demographic characteristics is certainly limited.

Additionally, since the data was sourced from only a single school district, students who transferred out of the district at any time after their freshmen year were excluded from the study’s graduation outcome data. The inability to track students once they transfer out of the

district may impact results due to the fact that “student mobility” is in itself an early warning indicator in a number of studies (Jimerson, Egeland, Sroufe, & Carlson, 2000).

One further limitation of this study was the timeframe of the study’s longitudinal data. Unfortunately, due to the availability of consistent and accurate student data, this study only analyzed the student cohorts spanning from 2015 to 2018. The four-year timeframe of the study is a relatively short span of time for the sample size. An extended timeframe would have enhanced the study’s findings and helped to mitigate any significant event that may have had an impact on the student results during that four-year period.

Delimitations

The first major delimitation of this study was the selection of the early warning indicators. As will be elaborated on in chapter two, educational researchers have analyzed the correlation of dropping out with a substantial number of different variables. Researchers have analyzed the predictive validity of graduation attainment with variables ranging from maternal educational attainment, to student substance abuse, to third-grade reading proficiency. This particular study incorporated the freshmen on-track indicator and chronic absenteeism variables for two primary reasons. First and foremost, these indicators were chosen because of the high predictive validity they have demonstrated in studies among urban and suburban student samples (Allensworth & Easton, 2007; Balfanz et al., 2007; Dalton et al., 2009; Johnson & Semmelroth, 2010; Suh et al., 2007). Secondly, both these variables are required to be reported to the Oregon Department of Education and readily accessible for Oregon educators.

The other major delimitation of this study was the manner in which the independent and dependent variables were defined. Nearly every major study has defined the “freshmen on-track” indicator in a slightly different manner, which is generally dependent on the state reporting

requirements in each particular state. While some states simply considered a freshmen on-track if a student earned a designated number of credits their freshmen year (Office of Accountability, Research, 2017), many other studies required a student to pass designated core classes in addition to earning a designated amount of credits to be considered on-track (Allensworth & Easton, 2005; Johnson & Semmelroth, 2010). Differing requirements for considering a freshmen on-track affect the degree to which studies can be compared. This particular study utilized the Oregon Department of Education definition for “freshmen on-track” (Oregon Department of Education, 2017).

Similar to defining the criteria that constitutes a freshmen on-track, selecting the student outcomes that classify a student as a “dropout” or “non-graduate” was a major delimitation of this study. The definition of what constitutes a “dropout” varies greatly from study to study and can substantially influence results (Bowers et al., 2013). Due to the great variation across the research literature, this study followed the guidelines that the Oregon Department of Education uses in their calculation for Oregon school graduation rates. Students who received a regular high school diploma, modified diploma, or participated in the post-graduate scholars’ program within four years of beginning high school were considered “four-year graduates.” Students who earned an adult high school diploma, extended diploma, or general education diploma (GED) were considered “completers” but “non-graduates.” Finally, students who received an alternative certificate, were continuing enrollment, or were non-completers/dropouts not continuing enrollment were considered “dropouts.” As will be elaborated in the Methodology section, “dropouts” and “non-graduates” were classified as “Non-Four-Year Graduates” for the data analysis. Applying the same rules that the state of Oregon utilizes in graduation calculations ensured that the results were consistent with the context from which they were retrieved.

A final delimitation of this study was related to the geographic classification of the school district. Schools districts are generally classified as either urban, suburban, or rural. The population cutoffs for these designations vary greatly from study to study. For this study, the National Center for Education Statistics (NCES) Common Core of Data (CCD) Public Elementary/Secondary School Locale Code definitions were used to categorize schools as rural, suburban, or urban. Based on the operationalized definition as a town with less than 25,000 residents, the Kentwood School District was considered “rural.”

Summary

Students who drop out of school face several negative outcomes personally, economically, and socially. To help prevent students from withdrawing from school, educational researchers have developed models to help predict the probability that a student will drop out. These models help educators identify at-risk students while there is still time to intervene. Although promising, several factors have prohibited the educational research field from establishing universal early warning indicators and thresholds. In addition, the clear majority of these studies were conducted with student sample populations from large, urban school districts.

This study sought to test the predictive validity of two variables identified by educational researchers as early warning indicators. Through analyzing the relationship that exists between four-year graduation and the freshmen on-track indicator, freshmen absenteeism, and student demographic variables, this study added to the current body of research regarding EWS effectiveness among a rural student population.

Chapter Two

Literature Review

This literature review begins with a section reviewing the development of early warning systems (EWS) as a response to the dropout problem. Within that section is an exploration of the national educational reforms of the last fifty years, the historical development of EWS, general characteristics of EWS, common critiques of EWS, and where EWS fits in the broader system of supporting students. The second major theme of the literature review is an analysis of the different variables commonly used within EWS. The section primarily focuses on the use of credit attainment, attendance, and demographic variables as early warning indicators. The final major theme of the literature review is an analysis of the issues that can influence a student's decision to drop out that exist specifically within rural schools and communities.

The Development of EWS in Response to the Dropout Problem

Each month, tens of thousands of students in the United States make the decision to no longer pursue a high school diploma (Mcfarland et al., 2017). Unfortunately, the decision to drop out of school negatively impacts a student's long-term economic and social well-being. Socially, non-graduates have higher rates of incarceration (Debaun & Roc, 2013; Harlow, 2003; Rumberger, 2011) and are more likely to rely on social welfare support programs for food, housing, and healthcare (Irving & Loveless, 2015). Additionally, dropouts have higher rates of mental illness (Hjorth et al., 2016) and are expected to die at a younger age than their peers who graduate (Hummer & Hernandez, 2017; Muller, 2002). Furthermore, non-graduates are also less likely to vote or participate in any form of civic engagement (Rumberger, 2011).

Economically, high school dropouts face an unemployment rate nearly twice as high as those who earn an associate's degree (U.S. Bureau of Labor and Statistics, 2014) and typically

earn less than half the median weekly income than those with a bachelor's degree (U.S. Bureau of Labor Statistics, 2016). Students who fail to graduate high school also suffer from a decreased capacity for occupational mobility (Kim, 2013). Additionally, the estimated lifetime earnings of a high school dropout are typically a quarter million dollars less than their peers who graduated high school (Levin, Belfield, & Rouse, 2007).

Not only does the decision to drop out negatively impact their own future, there are negative economic and social impacts that reverberate at national, state, and local levels. The reduced economic output of non-graduates results in a loss of potential state and national tax revenue (Levin et al., 2007), and increases the likelihood that dropouts will collect unemployment insurance and burden social support programs (Irving & Loveless, 2015; Levin et al., 2007). These negative economic and social impacts are amplified within rural communities, where there is less access to social support services, fewer professional job opportunities, and higher susceptibility to economic instability (Gibbs, 2002; Nadel & Sagaway, 2002; Paasch & Swaim, 1993; Tompkins & Deloney, 1994).

Given such significant negative impacts of dropping out of school, the last fifty years have seen school districts across the country implement several national and state-level initiatives to prevent students from dropping out and improve the quality of public schools. In the 1960s, educational leaders made dropout prevention a focal point within the educational field (Dorn, 2003). In the 1980's, the U.S. Department of Education's report, *A Nation At Risk: The Imperative for Educational Reform,* brought a renewed focus on the inadequacies of the American public school system and the need to reform (US Department of Education, 2008; National Commission on Excellence in Education, 1983). The 1990s and early 2000s saw the introduction of the *Improving America's Schools Act of 1994* and the *No Child Left Behind Act,*

which sought to raise standards and increase accountability for America's public education system. Although federal legislation brought a number of positive reforms to public education over the last fifty years, there continues to be mixed results regarding dropout prevention efforts throughout the late 20th century (Dorn, 2003; Montecel, Cortez, & Cortez, 2004; Toby, Armor, & Jim, 1992).

Historical Development of EWS

The call to develop accurate longitudinal data analysis methods to help predict students' likelihood to dropout can be traced back to the school reform movements of the late 1970s and 1980s (Roderick, 1993). As educational leaders sought to determine the best interventions to prevent at-risk students from dropping out of school, it became abundantly clear that dropout intervention strategies targeted at juniors and seniors in high school were too late to prevent students from dropping out (Finn, 1993; Rumberger, 1987). The longitudinal surveys of the 1980s simply described the factors that may have influenced students' educational experience retrospectively, offering a way to look back on what may have affected a student's educational success or failure (Lloyd, 1978; Pierret, 2005). Moving from retroactive data analysis, researchers saw the need to take a more active and precise analytic approach to the dropout process in order to be able to identify potential dropouts at an earlier stage in their academic career when successful intervention was still possible (Lloyd, 1978; Roderick, 1993; Rumberger, 1987).

Research has affirmed that a student's decision to drop out of school is not an erratic, singular decision but rather the summation of a long process of disengagement from the educational system (Jimerson et al., 2000; Paasch & Swaim, 1993; Pinkus, 2008). Since the decision to drop out is not made spontaneously, researchers in the late 1970s and 1980s began to

analyze different student variables that might provide a signal that a student was on the path to dropping out (Hess et al., 1985; Lloyd, 1978). These early models were groundbreaking but were also criticized for their lack of accuracy (Gleason & Dynarski, 2002; Roderick, 1993). Throughout the late 20th century, educational researchers further refined the use of longitudinal data techniques to explore which early warning indicators could be the most predictive at early ages (Alexander, Entwisle, & Horsey, 1997; Finn, 1993; Gleason & Dynarski, 2002; Jimerson et al., 2000; Rosenthal, 1998). This exploration and analysis led to the more modern-day practice of early warning systems.

The use of EWS to combat the dropout problem has rapidly expanded over the last two decades and has become a relatively common practice in school districts across the United States (Bruce et al., 2011; Henry, Knight, & Thornberry, 2012; Soland, 2013). With the expansion in popularity, further research on EWS techniques have led to an increase in the accuracy of identifying at-risk students (Allensworth & Easton, 2007). Along with identifying additional dropout indicators earlier in a student's educational career, current EWS research also focuses on combining multiple student variables (i.e. student absences, discipline incidents, and course failures) to increase the predictive capabilities of their models (Bowers, 2010; Bruce et al., 2011; Hammond, 2007; Henry et al., 2012).

Presently, EWS educational researchers are continuing to refine and review their methodologies and student variables in order to further strengthen educators' ability to identify the likelihood that a student will not graduate. Although still in its relative infancy, EWS has emerged as a powerful tool to assist school districts in providing timely and targeted support for the students who need it most.

Common Characteristics of EWS

While each EWS has distinct variables and methodologies, there are some common components of all EWS that are fundamental to their use. At the core of every EWS is the use of various student data variables to identify at-risk students (Bowers, 2010; Bruce et al., 2011; Hammond, 2007). Although the different types of data variables can range significantly based on each educational researcher (Bowers, 2010; Hammond, 2007), student data indicators are essential elements of EWS. The range in different data variables is primarily due to the various types of data that are accessible to each researcher and the unique focus of each EWS research study.

Another common characteristic of EWS is the frequency in which student data updates. Unlike the longitudinal data studies of the early 1980s that analyzed student data retrospectively (Hess et al., 1985; Rumberger, 1987), modern EWS are frequently updated with real-time student data (Bruce et al., 2011; Frazelle & Nagel, 2015; Mac Iver & Mac Iver, 2010). The timely updates of EWS are a particularly powerful practice, helping educators ensure intervention and supports are provided at the first signs of student academic or behavior disengagement from school (Frazelle & Nagel, 2015; Mac Iver & Mac Iver, 2010; Rumberger, 1987). Using inefficient and labor-intensive data collection techniques such as student surveys or teacher interviews within an EWS, can lead to slow and untimely updating. Unfortunately, without timely student data, EWS become merely a retrospective analysis rather than a powerful formative tool that can potentially identify and help educators intervene to prevent students from dropping out.

Common Critiques of EWS

While EWS can have a positive impact on providing targeted support to potential dropouts, they are not without their drawbacks. The most common critique of dropout prediction models is that they may misidentify students as dropouts or fail to identify particular students who actually dropped out (Bowers et al., 2013; Bruce et al., 2011; Gleason & Dynarski, 2002). Although there are some common themes across dropouts, each student’s dropout story is unique and therefore creating a model to accurately predict all dropouts is immeasurably complex. When describing the complexity of developing a dropout model that accurately identifies all potential dropouts, Gleason and Dynarski (2002) explain that a certain portion of students drop out, “… not because of the cumulative effects of poor academic performance but because of an unexpected event. A student may have become a parent, been arrested, started using drugs, or had serious personal problems at home (p. 39).” These unexpected, traumatic life events that can lead a student to drop out of school are generally not incorporated in to EWS data analysis and therefore have the potential to lead to misidentifications from EWS. Unfortunately, the value of EWS diminishes with each misidentification of a student. With that in mind, educational researchers have continued to analyze the predictive validity of particular early warning indicators at different age levels, settings, and samples in order to hone in on those variables with the highest predictive validity (Allensworth, 2013; Bowers et al., 2013; Mac Iver & Messel, 2013; Neild & Balfanz, 2006).

There is a balance between identifying at-risk students as early as possible in their academic career while at the same time ensuring that the correct students are identified as potential dropouts. The attempt to identify students as early as possible has led to mixed results in several studies. For example, Hernandez (2011) found that 16% of third-grade students who

were below grade level in reading at 3rd grade failed to graduate. While this information is useful to emphasize the importance of early literacy skills, its application as a dropout prediction model is limited. Similarly, Kuppersmidt and Coe (1990) found that excessive absences in 5th grade accounted for 27% of dropouts. Comparable to 3rd grade reading scores, this metric is not a reliable early warning indicator. Most impressively, Lloyd (1978) used nineteen factors to identify 70% of dropouts at the third-grade level. While impressive, Lloyd's (1978) model was based on data not readily available in most schools and misidentified 25% of graduates as dropouts.

While establishing the predictive validity of early warning indicators at the elementary level has proven difficult, moving up to a student's middle school years is not without complications either. Although Balfanz, Herzog, & Mac Iver (2007) were able to use 6th grade absenteeism, behavior marks, and course failures to predict 60% of potential non-graduates, Gleason and Dynarski (2002), analyzed 17 different middle school risk factors and concluded that, "…none of the single risk factors efficiently identified dropouts (pp. 35)." The mixed results of middle school early warning indicators reflect the difficulties of establishing a clear set of early warning indicators that have consistent predictive validity across different populations and settings.

Need for Districts to Develop Localized EWS

The need for school districts to develop localized EWS based on their available data and local needs has been echoed by a number of researchers (Balfanz et al., 2007; Frazelle & Barton, 2013; Gleason & Dynarski, 2002, 1998; Mac Iver & Mac Iver, 2010). While the "ABCs of dropping out" (attendance, behavior, and course performance) have emerged as a starting point of student variables in most EWS, there is not an established, one-size-fits all model for EWS

(Barfield, Hartman, & Knight, 2012; Bruce et al., 2011; Neild et al., 2007; Pinkus, 2008). Additionally, educational leaders have been encouraged to tailor their local EWS to the unique assortment of student data variables available in their particular local context (Bowers et al., 2013; Gleason & Dynarski, 2002; Johnson & Semmelroth, 2010; Stuit et al., 2016).

One major aspect of the call for districts to develop their own EWS is due to the variation in reporting requirements, definitions, and summative assessment systems utilized by each different state (Barfield et al., 2012; Bruce et al., 2011; Heppen & Therriault, 2008). Each state's department of education has a unique set of student variables that are reported to the state for various accountability purposes. Although each state is different, Heppen & Therriault (2008) recognize that "states can play a particularly significant role by helping to build and align the data systems necessary to track and prevent dropouts (p. 11)." Since EWS are most effective when data is frequently updated, the variation in state reporting requirements requires school districts to tailor their EWS to data variables that are readily available through their state reporting protocols (Frazelle & Nagel, 2015; Jerald, 2006; Knowles, 2016).

In addition to the variations in reporting requirements for different states, another primary reason for districts to develop their own EWS is the varying graduation requirements and definitions across particular districts and states (Bowers et al., 2013; Jordan, Genti, & Mykerezi, 2012; Knowles, 2016). Each state has unique graduation requirements and rules governing the different types of diplomas awarded (Swanson & Chaplin, 2003). In addition, each state has their own unique, nuanced definitions for key terms associated with early warning system. For example, Oregon defines a freshmen on-track if the student has earned six total credits by the start of their sophomore year (Office of Accountability, Research, 2017), while Illinois requires students to earn five total semester credits and not fail any core class to be considered a freshmen

on-track (Illinois Department of Education, 2017). The variation in graduation requirements and definitions from state to state means that EWS cannot use a generic credit attainment count or assessment score, but rather must be tailored to match the unique needs of their local context.

Customizing local EWS to take into account the unique variations in state and local reporting requirements, definitions, and local assessment standards will help to create EWS that are more accurate at identifying at-risk students (Bowers et al., 2013; Neild & Balfanz, 2006; Paasch & Swaim, 1993; Pinkus, 2008; Strange, 2011; Stuit et al., 2016). Districts must also explore the unique academic performance standards, societal characteristics, and variables with the highest correlation of past students dropout (Heppen & Therriault, 2008).

EWS Role Within the Broader System of Student Support

While critically important, analyzing early warning indicators to identify potentially non-graduates is only the first step in a much broader system of supporting students. Selecting and analyzing the student variables with the highest predictive validity will have little value for at-risk students if it is not matched with effective interventions, proper resources, and practitioners that are capable of delivering the appropriate support to students (Montecel et al., 2004). With this is mind, it is crucial to observe the larger system of support to which EWS fall into. Bruce, Bridgeland, Balfanz, and Horning Fox (2011), explain that the most effective EWS are stationed within a larger student support framework that provides,

> "…rapid identification of students who are in trouble; rapid interventions that are targeted to students' immediate and longer-term need for support, redirection and greater success; the frequent monitoring of the success of interventions; a rapid modification of interventions that are not working; and shared learning from outcomes (Bruce et al., 2011, p. 11)."

These systems are situated in a boarder framework to move beyond the identification of students with potential risk factors to pairing the students with need-based support.

Once a student has been deemed at-risk through data analysis, effective support systems match the student's need with the proper intervention or support. Whether the support is academic, social, or emotional in nature, providing targeted intervention is essential for improving student outcomes (Greenberg et al., 2003). Academic interventions can help shore up a student's academic deficiencies so the student can accumulate credit. Social supports may include providing tangible services to meet the student and their family's physical needs. Finally, emotional interventions target a student's behavioral needs to aide in the student's overall mental well-being.

Finally, EWS can serve as a powerful indicator for aligning district and school-level resources where they are needed most. Through analyzing EWS data to identifying broader themes and demographic groups that are in need, school districts can better allocate resources and support to the highest need areas. This broader view of EWS utilization can serve as a catalyst for address the long-term social and ecological disparities that are found at the core of student need (Gleason & Dynarski, 2002).

Development of EWS Concluding Thoughts

Although still a relatively new educational practice, EWS have emerged as a promising practice to help educators identify students at-risk of failing to graduate while there is still time to intervene. Districts that develop their own EWS to identify and intervene for students at-risk of potentially dropping out will have a powerful tool to provide more precise interventions for students who need the most support. The need to distinguish the student variables that have the

highest predictive capabilities is an essential element of the EWS process and is the focus of the remainder of this literature review.

Student Variables and Methodologies Used in Early Warning Systems

Within the field of early warning systems, researchers have incorporated a wide variety of variables as early warning indicators identifying students who are at-risk of dropping out (Bowers et al., 2013; Pinkus, 2008). The assortment of student variables used in EWS are generally broken down into three primary categories; academic, behavioral, and demographic. This section discusses these three major categories of variables that are commonly incorporated into EWS. The variables used by researchers in EWS vary greatly both in the age level and the specific type of metric. By examining a variety of different academic, behavioral, and demographic indicators, researchers have been able to affirm the predictive validity of specific variables for graduation attainment.

Measuring Student Academic Performance

Various definitions and measures of student academic performance are a common feature of EWS. A student's academic performance in their classes, as may be expected, has been established as a strong signal as to whether or not that student will graduate (Bowers et al., 2013; Kennelly & Monrad, 2007; Neild & Balfanz, 2006). In order to quantify and measure a student's academic performance, educational researchers have utilized a number of different metrics. The primary academic performance variables seen in the research literature are credit attainment (Allensworth & Easton, 2007; Allensworth & Easton, 2005; Heppen & Therriault, 2008), course grades (Allensworth & Easton, 2007; Balfanz et al., 2007; Bruce et al., 2011; Ensminger & Slusarcick, 1992b; Gleason & Dynarski, 2002), assessment scores (Dalton, Glennie, & Ingels, 2009; Franklin & Trouard, 2016; Mac Iver & Messel, 2013), and GPA (Bowers, 2010; Bruce et

al., 2011; Burke, 2015; Mac Iver & Messel, 2013). While distinctively different metrics, course grades, credit attainment, and GPA are all deeply intertwined. For example, receiving a failing course grade will reduce a student's total credit attainment while also lowering their GPA. These three academic variables are dependent upon one another. Additionally, the use of these academic performance variables has been utilized by educational researchers at different points along a students' educational career.

Course failures. Academic grades from all stages of a student's educational career have been used for EWS. At the elementary level, researchers have incorporated a variety of course grades and marks to identify at-risk students with mixed results. Beginning as early as the first-grade, multiple researchers have established correlations between students' grades and future graduation attainment (Alexander et al., 1997; Ensminger & Slusarcick, 1992). In particular, Ensminger & Slusarscick (1992a) demonstrated that first grade students who receive "A's and "B's in arithmetic had almost twice the odds of graduating from high school than their peers who receive "C's and "D's. Researchers have also established correlations between course marks and graduation attainment during the intermediate grades (Lloyd, 1978; Roderick, 1993). While a number of researchers have found a correlation between elementary grades and dropping out, the results are not absolute. Kupersmidt and Coie (1990) did not find low fifth-grade course marks as a reliable predictor that a student would drop out of school. This discrepancy can most likely be attributed to the small sample size (n=112) of Kupersmidt and Coie's (1990) study and speaks to the different results of early warning indicators observed in different samples and settings.

Although students do not begin accumulating credits towards graduation until they begin high school, middle school English and math course failures are regular variables observed in EWS and have been shown to be a moderately reliable predictor of high school graduation

attainment. A number of research studies have affirmed that sixth-grade math or English failures have a strong correlation with future dropouts (Balfanz et al., 2007; Neild et al., 2007). Failing course grades in the 8th grade has shown a particularly strong relationship with dropping out (Neild et al., 2007; Stuit et al., 2016). The predicative capabilities of a failing grade in math or English during 8th grade in one study equated to a 75% probability that a student would drop out (Neild & Balfanz, 2006). Most recently, Stuit and Normby (2016) affirmed earlier research in determining that failing two or more courses during a student's 8th grade year was a strong indicator for predicting students' future failure to graduate. Finally, EWS researchers using longitudinal data have determined that students who graduated on time received less than half the number of "D's and "F's in middle school than students who failed to graduate on time (Saunders et al., 2008).

At the high school level, course failures, which are directly connected with credit attainment, have also been determined to have a strong correlation with graduation attainment. Research has shown that freshmen year course grades have a strong predictive validity for graduation attainment (Allensworth & Easton, 2007; Mac Iver & Messel, 2013; Saunders et al., 2008; Stuit & Norbury, 2016). In one study, researchers were able to use the total number of course failures from a student's freshmen year to identify 89% of the students that would later go on to graduate within four years (Allensworth & Easton, 2007). High school math and English course grades in particular have been shown to be strong indicators of future dropouts (Saunders et al., 2008; Uekawa et al., 2010). Uekawa, Merola, Fernandez, and Prowski (2010) determined that math and English course grades were one of the strongest predictors for students at-risk for dropping out in their study of roughly 40,000 Delaware high school students. The predictive

capabilities of student course grades is an essential academic variable to incorporate into an EWS.

Credit attainment. A focus of this study, which coincides with the practice of incorporating course failures in EWS, is the use of tracking the total number of credits earned by a student as a dropout indicator academic variable. Researchers commonly refer to a student as either being “on-track” for graduation or “off-track,” depending on whether or not the student has earned the appropriate number of credits necessary to graduate within four years (Allensworth & Easton, 2007; Dalton, Glennie, & Ingels, 2009; Johnson & Semmelroth, 2010). In general, a student is considered “on-track” if they have earned 25% of the total credits needed to graduate after their freshmen year and “off-track” if they have earned less than 25% of the total credits needed to graduate after their freshmen year.

Implementing credit attainment as a dropout indicator has emerged as a common academic variable featured in EWS. Similar to course grades, the “on-track” indicator has been found to be particularly predictive during students’ freshmen year. Research has shown that whether a student is “on-track” or “off-track” after their freshmen year is one of the strongest predictors of whether or not the student will graduate within four years (Allensworth & Easton, 2007; Johnson & Semmelroth, 2010). Allensworth and Easton (2007) found that a student’s freshmen “on-track” or “off-track” status had an overall accurate on-time graduation prediction rate of 80% (Allensworth & Easton, 2007). Similarly, Stuit, O’Cummings, Norbury, Heppen, Dhillon, Lindsay, and Zhu (2006) found in their study of three different Ohio school districts that the freshmen off-track indicator was the second highest single predictor that a student would not graduate.

Research has also shown that sophomore credit totals are predictive of graduation attainment (Dalton et al., 2009). Using the Educational Longitudinal Study of 2002 with roughly 13,000 sophomore students, Dalton et al., (2009) determined that 55% of sophomores who had earned less than ten credits failed to graduate compared to only 4% of sophomores who earned more than ten credits.

GPA. Intertwined with credit totals and course grades, several researchers have focused their study on the use of GPA as an early warning indicator. When a student fails a high school class, their expected credit attainment and GPA are lowered. Multiple studies have affirmed that a ninth-grade cumulative GPA < 2.0 is a strong indicator that a student will likely not graduate within four years (Burke, 2015; Johnson & Semmelroth, 2010; Stuit et al., 2016). Allensworth and Easton (2007) found that a student's freshmen year cumulative GPA could correctly predict whether or not a student would graduate 80% of the time (Allensworth & Easton, 2007).

Other researchers have focused on students' eighth-grade year cumulative GPA to serve as a dropout indicator (Burke, 2015; Mac Iver & Messel, 2013) Locally, Burke's (2015) study of 6100 students across four different school districts in Oregon found that a cumulative GPA <2.0 at the eighth-grade was a strong indicator of students at-risk of dropping out. Eighth-grade cumulative GPA was found to not only be strongly correlated with high school graduation but college enrollment as well (Mac Iver & Messel, 2013).

While a number of researchers have focused solely on the connection between eighth- and ninth-grade cumulative GPA with graduation attainment, many other researchers have found correlations between students' GPAs among other age ranges. A number of studies have established moderate correlations between students' GPA and graduation attainment ranging from 3rd grade to 12th grade (Eckstein & Wolpin, 1999; Lloyd, 1978; Rumberger & Palardy,

2005; Suh, Suh, & Houston, 2007). While 8^{th} and 9^{th} grade cumulative GPA have been shown to have strong correlation with graduation attainment, various other age ranges have demonstrated some promise as dropout indicators.

Incorporating specific academic performance variables into an EWS is a promising practice in helping educators provide more timely and targeted interventions for at-risk students. Although seemingly intertwined, research has shown that course grades, credit attainment, and GPA to be moderate effective dropout indicators at various points along a student's educational career. For educators seeking to develop a localized EWS, academic performance variables should be a key component of their model.

Behavior Variables

In addition to using academic performance variables to identify students at-risk of dropping out, educational researchers have also identified several behavioral variables that have demonstrated varying levels of correlation with dropping out. Behavior variables used in EWS vary greatly, ranging from student discipline incidents (Balfanz et al., 2007; Bruce et al., 2011; Burke, 2015; Finn, 1993) to behavior marks (Neild et al., 2007) to attendance rates (Allensworth & Easton, 2007; Balfanz et al., 2007; Barry & Reschly, 2012; Burke, 2015; Johnson & Semmelroth, 2010; Mac Iver, 2013; Mac Iver & Messel, 2013). This study's student behavioral variable is freshmen student absenteeism. Similar to the intertwining of student academic performance variables, student behavioral variables are also interrelated. For example, a student's dislike of school may cause the student to engage in negative behaviors leading to discipline which can then lead to a lack of desire to attend school. Schonberger (2012) notes, "Poor attendance may suggest that students are uninterested in the educational environment,

have competing interests outside of school, or that their family's resources may be impeding their ability to attend school on a consistent basis (p. 1)."

Attendance variables. Student absenteeism is a behavioral variable commonly used in EWS. Although student absenteeism has been measured using a variety of different standards and metrics, researchers have overwhelmingly established that students with poor attendance have a strong correlation with dropping out (Allensworth & Easton, 2007; Balfanz et al., 2007; Burke, 2015; Gleason & Dynarski, 1998; Kupersmidt & Coie, 1990; Mac Iver & Messel, 2013; Stuit et al., 2016; Suh et al., 2007). The definition of chronic absenteeism varies greatly from study to study and from state to state. For example, the Balfanz (2007) study defined poor attendance as missing 80% or more school days, Allensworth & Easton (2007) defined high absenteeism as missing more than one month of school per semester, and Neild & Balfanz (2006) defined absenteeism as missing 70% of the school year. In Oregon, chronic absenteeism is defined as missing 10% or more of the school days in one academic year (Oregon Department of Education, 2015).

Regardless of exact definition, the correlation between poor attendance and dropping out has been observed at all stages of a student's educational career. At the elementary level, Kupersmidt and Coie (1990) found fifth-grade truancy (defined as students who missed 15 or more days in an academic year) to be a reliable predictor for who would drop out. Consistent school attendance at the middle school level has also been established as a crucial factor for students to graduate on time (Balfanz et al., 2007; Gleason & Dynarski, 1998; Stuit et al., 2016). Notably, Balfanz, Herzog, & MacIver (2007) found 75% of the nearly 13,000 sixth grade students in their study who had attendance rates less than 80% failed to graduate high school on time.

Similarly, poor attendance at the high school is a strong dropout indicator. In particular, researchers have determined that freshmen year attendance is especially crucial for on-time graduation (Allensworth & Easton, 2005; Burke, 2015; Mac Iver & Messel, 2013). Tracking attendance the first month of a student's freshmen year has proven to be an especially powerful early warning indicator (Allensworth & Easton, 2007). Through using logistical regression analysis, Allensworth and Easton (2007) found that only 21% of students who missed more than fifteen days of their freshmen year graduated within four years. Likewise, Burke (2015) found that 83% of freshmen students with attendance rates lower than 80% did not graduate on time. Confirming the importance of freshmen year attendance, Neild and Balfanz (2006) found freshmen attendance to be a stronger predictor of on-time graduation than gender, race or ethnicity, age, and test scores. Additionally, Gleason & Dynarski (2002) found high absenteeism as the highest risk factor of the 17 factors they analyzed in their early warning indicator study (Gleason & Dynarski, 2002).

Demographic Variables

The third and final category of student variables commonly incorporated in EWS is demographic variables. The primary demographic variables analyzed in EWS research are those variables that schools are required to report according to state and federal law (i.e. ethnicity and race, gender, EEL, SES, TAG, SPED). While these variables are clearly less malleable than academic and behavioral variables, they are commonly analyzed and reported in EWS research.

Ethnicity & race. Several studies have shown ethnicity to have varying levels of correlation with graduation rates. In multiple studies, students classified as Asian have had higher graduation rates compared to other races/ethnicities (Burke, 2015; Hess et al., 1985; Neild & Balfanz, 2006; Uekawa et al., 2010). Conversely, studies have found students classified as

African American, Native American, or Latino have lower-than-average graduation rates (Burke, 2015; Dalton et al., 2009; Neild & Balfanz, 2006; Saunders et al., 2008; Uekawa et al., 2010).

Gender. Similar to ethnicity and racial subgroups, gender differences have proven to have consistent correlation in regards to graduation rates across a wide range of research studies. A number of researchers have established that females have a slightly higher graduation rate than their male counterparts (Burke, 2015; Dalton et al., 2009; Roderick, 1993; Soland, 2013; Uekawa et al., 2010). Specifically, Burke (2015) found that male students were 1.6 times more likely to dropout than females.

Other educational classifications. In addition to race, ethnicity, and gender, numerous other demographic classifications are commonly incorporated in EWS. Special Education (SPED) identification has proven to be associated with a higher likelihood that a student will drop out (Balfanz et al., 2007; Burke, 2015; Uekawa et al., 2010). Burke (2015) found that SPED students dropped out at a rate twice as high than non-SPED students. Similarly, Balfanz, Herzog, & MacIver (2007) found that SPED identification significantly reduces the likelihood that a student would graduate high school on time. Most alarming, in the *Twenty-Third Annual Report to Congress on the Implementation of the Individuals with Disabilities Education Act* (2001) researchers found that nearly 50% of all students identified as having an emotional or behavioral disability failed to graduate high school (U.S. Department of Education, 2001).

Student classification as either Limited English Proficient (LEP) or English Language Learner (ELL) is another demographic variable tracked in many EWS. Parallel to SPED identification, research has shown that ELL classification corresponds to higher dropout rates (Allensworth & Easton, 2012; Balfanz et al., 2007; Saunders et al., 2008). Saunders, Silver, & Zarate (2008) found that only one-third of students designated as Limited English Proficiency

(LEP) graduated within four years (Saunders et al., 2008). Similarly, Rumberger (1995) found that students from non-English speaking families had significantly higher odds of failing to graduate high school compared to their peers.

Family characteristics. Educational researchers have also incorporated several variables related to a student's family into EWS. The primary familial demographic variable most often analyzed in EWS research that has shown to have a moderately strong correlation with graduation rates is the socioeconomic status (SES) of a student's family (Dalton et al., 2009; Ensminger & Slusarcick, 1992a; Franklin & Trouard, 2016; Hernandez, 2011; Paasch & Swaim, 1993; Saunders et al., 2008; Suh et al., 2007). The research literature, as explained by Roscignio, Tomaskovic-Devey, & Crowley (2006) has, "…repeatedly shown, socioeconomic status of a student's household is consistently influential for both achievement and attainment" (p. 2112). Alexander, Saunders, Silver, & Zarate (2008) found that only 48% of the study's 45,000 freshmen students who qualified for free and reduced lunch graduated on time. Similarly, Dalton et al., (2009) established that 77% of all dropouts came from families who were in the lower half of socioeconomic distribution. The connection between SES and dropping out is so well-documented that Schoeneberger, (2012) declared, "most ubiquitously explored in the literature is the association between student decisions to drop out and their families' level of income, or socioeconomic status (p. 8)."

Combining Multiple Indicators to Increase Predictive Validity

A common technique utilized by EWS researchers to increase the predictive validity of their models is to identify students flagged by multiple early warning indicators. While at-risk identification through a single early warning indicator can certainly be informative, identifying

at-risk students by using multiple early warning indicators helps increase the predictive validity of EWS models (Balfanz et al., 2007; Gleason & Dynarski, 2002; Suh et al., 2007).

EWS Methodologies

Proper statistical analysis is an essential element of EWS. Once suitable academic, behavior, and demographic variables have been identified, educational researchers have incorporated a wide variety of statistical tools to appropriately identify at-risk students. Multiple and multilevel logistic regression is a common model used for the statistical analysis of EWS. Multiple logistic regression is an appropriate fit for EWS statistical analysis because the model calculates the relationship between one, dichotomous dependent variable (i.e. graduate vs. non-graduate) and multiple nominal (i.e. ethnicity) or ordinal (i.e. GPA, Grades) independent variables (Franklin & Trouard, 2016; Koon & Petscher, 2015; Stuit et al., 2016; Suh et al., 2007). Chi-square analysis is also commonly incorporated in EWS statistical analysis to determine if a study's null-hypothesis can be rejected (Bowers, 2010; Eckstein & Wolpin, 1999; Stuit et al., 2016; Uekawa et al., 2010). Additionally, receiver operative characteristics (ROC) have recently become common in EWS statistical practices to evaluate the accuracy and thresholds for specific dropout indicators (Bowers et al., 2013; Gleason & Dynarski, 2002).

Concluding Thoughts

While there have been mixed results regarding the predictive capabilities for graduation for several behavior and demographic variables, several variables within those categories have demonstrated promise in identifying potential dropouts and would serve well as indicators within an EWS. In addition, multiple logistical regression models have been shown to be an effective method for determining which variables are statistically significant.

In conclusion, EWS have emerged as a prominent tool used to assist educators in identifying students needing targeted support while time remains to intervene. With variations observed in the predictive capabilities of different academic, behavior, and demographic variables, it is important for school districts to identify the variables that have had the highest correlation with dropouts amongst their unique student populations. While variations exist, research has established a collection of variables that have shown promising abilities to pinpoint students at risk. Through determining highly predictive student variables and connecting identified at-risk students with timely interventions, school districts can utilize EWS to potentially reduce dropout rates and increase four-year graduation rates.

Issues Impacting Graduation Attainment in Rural Education Setting

The social and economic factors corresponding with geographic setting arise as a major theme in the research literature regarding student dropouts (Christenson & Thurlow, 2004; Hardre & Reeve, 2003; Johnson & Madden, 2010; Roscigno et al., 2006). With local context being a major influencer in the predictive validity, cut scores, and availability of early warning indicators (Johnson & Semmelroth, 2010), it is important to understand the unique characteristics of rural students, schools, and communities, along with the role those factors play in influencing a student's educational trajectory. As described by Christianson (2004), "The problem of school dropout cannot be understood in isolation from contextual factors. Early school withdrawal reflects a complex interplay among student, family, school, and community variables… (p. 37)." With that in mind, it is crucial to explore the common social and economic characteristics of rural communities and how they may influence the educational decisions of rural students.

Defining Rural Communities

EWS researchers generally classify the geographic setting of schools into three major categories; suburban, urban, or rural (Gleason & Dynarski, 2002; Hu, 2003; Jordan et al., 2012; Rumberger, 1995). While three primary categories exist, the definition and measures used to classify each geographic setting vary greatly from study to study. The differing definitions of geographic categories makes drawing comparison from one study to another very difficult. This is especially true regarding rural settings, as a tremendous degree of variation exists in the definitions of “rural.” For example, the US Census Bureau classifies “rural” as any area outside of an urban cluster with a population density greater than 2,500 residents (Ratcliffe, Burd, Holder, & Fields, 2016), while the Office of Management and Budget (OMB) simply classifies all areas with less than 50,000 residents as non-metro (Office of Management and Budget, 2010). Monk (2007) explains that simply defining rural as not urban or suburban “overlooks the complexity of rural communities and school districts, as well as the considerable variation within them” (p. 156). While difficult to generalize all rural communities, there do exist a number of positive and negative general characteristics that are commonly observed in nearly all rural communities.

Geographically, rural communities are characterized by sparse settlement (Johnson, 2005; Malhoit, 2005), a large distance from an urban center (>50 miles) (Monk, 2007, Johnson, 2005), and a relatively small population size compared to urban areas (Ratcliffe et al., 2016). Economically, rural communities are typically dependent on agriculture, natural resource extraction, or tourism industries (Byun, Meece, Irvin, & Hutchins, 2012; Gibbs, 2002; Monk, 2007). They are also characteristically lacking in professional job opportunities (Gibbs, 2002; Paasch & Swaim, 1993), with high rates of poverty (Byun et al., 2012; Johnson, 2005; Nadel &

Sagaway, 2002; Roscigno et al., 2006). Socially, these communities often have high levels of community engagement (Bauch, 2001; Malhoit, 2005) but lack choices for consumer and social services (i.e. healthcare, schooling, and shopping) (Helge, 1991; Johnson, 2005; Nadel & Sagaway, 2002).

Issues Influencing Rural Students' Educational Choices

While each student's journey to dropping out is unique, research has found that most students' decision to drop out is rooted in issues related to their school, family, or work situations (Rumberger, 2011). Unfortunately, some of the common characteristics shared by rural communities relating to these three main categories can have a negative impact on students' educational choices. Although the definition of what constitutes a "rural school" has led to some discrepancies in the reporting of exact graduation rates (Jordan et al., 2012), the research literature shows that students from rural schools generally experience higher rates of dropping out and lower levels of academic achievement compared to their suburban peers (Hardre & Reeve, 2003; Jordan et al., 2012; Paasch & Swaim, 1993; Roscigno & Crowley, 2001; Roscigno et al., 2006). The higher rate of non-graduation observed in rural communities can most likely be attributed to several interrelated factors facing rural students, schools, and communities. These issues are typically classified as either "pull-out" or "push-out" factors (Boylan & Renzulli, 2017; Stearns & Glennie, 2006). "Pull-out" factors are circumstances that are external to school that may entice or require a student to drop out (Boylan & Renzulli, 2017). This includes withdrawing from school due to the perceived benefits of obtaining a job or due to a familial responsibility. "Push-out" factors relate to internal school issues that may cause a student to drop out. Conflicts with teachers/administrators, disinterest in academic coursework, or disciplinary incidents are common push-out factors (Stearns & Glennie, 2006).

Rural dropout issues relating to employment industries. The types of jobs typically available in rural communities may serve as a pull-out factor, which negatively influences a student's decision to remain in school (Gibbs, 2002; Nadel & Sagaway, 2002; Paasch & Swaim, 1993). Local economies based on agriculture, natural resource extraction, and basic manufacturing typically do not require students to pursue higher education to obtain employment. Since a high school diploma or college degree is likely not required for employment in these industries, students in rural communities may be more prone to drop out because of the perceived opportunity costs of staying in school (Paasch & Swaim, 1993; Stearns & Glennie, 2006). Gibbs (2002) explains, "Rural production is often more routinized, demanding less training or education. Over time, rural areas have retrained a relatively large share of the nation's low-skill, low-technology industries and less-skill occupations" (p. 56). Additionally, the multi-generational engagement in low-skill agriculture and manufacturing jobs typically seen in rural communities can influence rural students and families to devalue higher education and settle for low-skill jobs (Gibbs, 2002; Reid, 1989).

Rural family characteristics. Family characteristics have also been shown to play a major role in influencing the educational choices of students (Jimerson et al., 2000; Rumberger, 2011). Although family units have traditionally been more intact in rural areas compared to urban settings, rural communities are now seeing the same rates of single parent households as their non-rural counterparts (Lichter & Egeebeen, 1992; Roscigno & Crowley, 2001). Additionally, the larger family sizes often seen in rural communities can require rural students to take on more household and childcare responsibilities (Roscigno & Crowley, 2001). This is especially problematic since students that come from single parent households with high numbers of siblings are shown to be less likely to graduate (Coleman, 1988). The increased

responsibility of rural students to take care of younger siblings can serve as a direct pull-out factor.

Another major familial characteristic that can serve as a pull-out factor is teen pregnancy and parenthood (Dalton et al., 2009; Mac Iver, 2013; Rumberger & Lim, 2008). Unfortunately, teenage pregnancy rates are higher in low-income, rural communities (Helge, 1991; Nadel & Sagaway, 2002). As healthcare and social service supports are less prevalent in rural communities, the pull-out factor of teenage pregnancy is amplified (Johnson, 2005; Nadel & Sagaway, 2002; Paasch & Swaim, 1993).

Rural school challenges. Researchers have identified several benefits of small rural school settings. Conditions such as smaller teacher/student ratios, higher levels of teacher autonomy and work satisfaction, as well as an increased sense of community, are all favorable elements typifying rural schools (Gibbs, 2000; Johnson, 2005; Monk, 2007). While these characteristics most certainly play a positive role in the educational experiences of rural school students, there also exists several challenges directly related to rural school settings.

In addition to the push-out and pull-out factors seen because of rural economic and familial issues, rural students also face a number of challenges in school that are not experienced by suburban students. These barriers are primarily rooted in the lack of resources and services available in smaller communities. Knoblauch & Chase (2015) explain, “Based on the research literature, it seems as if rural and urban schools face more challenges regarding funding, resources, teacher quality and supply, and disciplinary problems than do suburban schools” (p. 106). The inability to receive proper funding and support has been shown to lead to several damaging impacts for rural schools and communities.

Teacher quality & training. The quality of a student's teachers has a tremendous impact on a student's potential academic success (Darling-Hammond, 2000). Unfortunately, rural schools are more likely to have younger, possibly underprepared teachers, who are less likely to have a graduate degree compared to their non-rural counterparts (Bauch, 2001; Carlsen & Monk, 1992; Gibbs, 2000; Monk, 2007). Roughly one third of rural school teachers have obtained a graduate degree compared to nearly half of urban school teachers (Gibbs, 2000). Additionally, properly equipping teachers to improve their practices through professional development in rural communities can be difficult due to geographic isolation (Arnold, 2004; Malhoit, 2005). One impact of the lack of highly trained teachers in rural schools is a reduction in the number of advanced courses and special programs that rural schools are able to offer their students (Bauch, 2001; Greenberg & Teixeira, 1998). The lack of specialized programs and advanced courses in rural schools can potentially lead students to become disengaged from school. Fortunately, recent technological advancements in online education have helped rural schools begin to offer more advanced classes online (Johnson, 2005).

Not only is the lack of highly-trained teachers a problem for rural schools, recruiting and retaining teachers can be a critical issue in rural communities (Johnson, 2005; Lowe, 2006; Monk, 2007). Lack of teacher retention can lead to high teacher turnover, which has proven to negatively impact student achievement (Ronfeldt, Loeb, & Wyckoff, 2013). The challenges relating to teacher retainment have led many rural school districts to offer teacher loan forgiveness as well as provide teacher housing (Lowe, 2006; Malhoit, 2005).

Finally, the smaller scale of rural schools compared to that of large urban or suburban schools has an impact on the depth and level of support services that rural schools can offer their students. This reduced scale leads to fewer financial, administrative, and intuitional resources are

available to provide support services for students in need of additional educational assistance (Helge, 1991; Monk, 2007; Schafft, 2006). The potential lack of adequate support services for special education students and English language learners is troubling since rural schools are more likely to have more students deemed at-risk due to poverty, special education status, and mobility (Johnson, 2005; Malhoit, 2005; Nadel & Sagaway, 2002; Schafft, 2006). With the relatively recent growth of non-native English speaking students moving to rural communities due to agricultural employment opportunities, rural schools are often faced without staff properly qualified to deliver ELL services (Johnson, 2005).

Rural students' higher education aspirations. A student's desire or aspiration for higher education plays a major role in the student's ability to persist through high school and pursue a college degree (Byun et al., 2012; Hu, 2003). Studies have found that students from rural schools have lower aspirations to pursue a four-year degree or graduate degrees than urban and suburban students (Haller & Virkler, 1993; Hu, 2003). The lack of post-secondary aspirations can be attributed to several issues experienced by rural students that are not experienced by their non-rural peers. Foremost, parents of rural students are less likely to have attended college themselves, which is a key predictor of college enrollment (Gibbs, 2000). This may also be a contributing factor in Roscigno and Crowle's (2006) finding that rural parents typically had lower educational expectations for their children. Additionally, with higher poverty levels observed in rural communities, the cost of higher education can also be a barrier for rural families (Gibbs, 2000). With lower rates of personal experience in higher education, a lack of professional jobs that require higher education, and lower education, rural families are less likely invest in, or see the value of higher education (Roscigno et al., 2006). Other theories suggest that

rural students' lower aspiration for higher education is possibly due to students' loyalty to their community and strong sense of place (Hektner, 1995; Howley, 2006)

Relative Lack of Educational Research in Rural Settings

One final disadvantage for students within a rural education setting is the relative lack of educational research conducted regarding rural student populations compared to non-rural (Coladarci, 2007; Hardre, Crowson, Debacker, & White, 2007; Johnson, 2005; Reid, 1989). Despite nearly twenty-four percent of all public school students being enrolled in schools within rural areas (National Center for Education Statistics, 2013) research regarding rural education represents only a slim fraction of the research literature (Coladarci, 2007; Gandara, Gutiaez, & O'Hara, 2001). Reid (1989) explains, "While (non-rural) areas have think tanks and blue-ribbon commissions to study their problems, rural communities usually fly by the seats of their pants…" (p. 22).

This lack of educational research in rural areas is particularly apparent in regards to EWS and early warning indicators. Although EWS have grown in popularity over the last two decades, there remain a relatively small number of studies that have examined the predictive validity of common early warning indicators in rural populations (Johnson & Semmelroth, 2010). The preeminent EWS research pertaining to EWS has taken place, "…in heavily urbanized contexts such as Philadelphia and Chicago" (Johnson & Semmelroth, 2010, p. 10). This lack of research regarding the predictive validity of specific early warning indicators could be substantial as rural students clearly have a number of unique challenges and barriers related to their graduation attainment.

Concluding Thoughts

While rural school and community settings offer a number of benefits, there also exist a number of factors that may negatively impact rural students' educational trajectories. A limited local economic outlook, familial demands, limited school resources, and lower post-secondary school aspirations can all serve as push-out or pull-out factors causing rural students to drop out of school. Additionally, the relative lack of educational research conducted with rural populations compared to urban and suburban makes drawing conclusions and generalizations about rural student populations difficult.

Chapter Three

Methodology

This study was a quantitative, ex post facto, longitudinal study using secondary data. Binomial logistic regression was used to measure the extent to which Oregon's freshmen on-track indicator, freshmen absenteeism, and specific demographic variables served as valid predictors of four-year graduation attainment in a rural Oregon school district.

The research questions addressed through this study were:

1) To what extent did the freshmen on-track indicator status predict the probability that a student graduated within four years?
2) To what extent did the total number of days a student was absent their freshmen year predict the probability that the student graduated within four years?
3) To what extent did combining a student's freshmen on-track indicator status and total number of days absent their freshmen year, predict the probability that the student graduated within four years?
4) To what extent did the freshmen on-track indicator status, total number of days a student was absent their freshmen year, and demographic variables (gender, race/ethnicity, SPED, LEP, and SES) predict the probability of four-year graduation attainment?

Sample

The target population of this study was all Kentwood School District students. For the 2017-2018 school year, the school district served 2,870 total students. Of those students, 76% were White, 16% Hispanic/Latino, 6% Multiracial, 1% Asian, 1% American India, and <1% Native Hawaiian/Pacific Islander or Black/African American. Additionally, 9% of the students

were classified as Ever English Learners, 14% were Students with Disabilities, and 61% qualified for free/reduced lunch. The school district served the student population for the entire county. According to the 2010 US Census, 48% of the county's residents were classified as rural (US Census Bureau, 2010). For that particular census, the bureau's definition of 'rural' "encompasses all population, housing, and territory not included within an urban area…To qualify as an urban area, the territory identified according to criteria must encompass at least 2,500 people, at least 1,500 of which reside outside institutional group quarters (US Census Bureau, 2010)."

The convenience sample for the study consisted of the student cohorts ranging from 2015-2018 from the Kentwood School District. This sample was composed of 731 students who attended one of the four high school programs in the district during those years. Those programs included a traditional 5A high school, a small alternative high school, a GED program, and an online school. All students who were enrolled in the Kentwood School District their freshmen year and went on to receive their final exit code ("4 Year Graduate" or "Non-4 Year Graduate") from the district were included in the sample.

Variables

The variables in this study were selected based on a thorough review of the EWS research literature. EWS variables should be chosen based on their proven predictive ability as well as their local availability (Bruce et al., 2011; Gleason & Dynarski, 2002; Johnson & Semmelroth, 2010). The following independent and dependent variables were selected and operationalized for this study.

Independent predictor variables. The first independent variable in this study was a dichotomous, nominal variable termed the "Freshmen On-Track Indicator." Oregon school

districts were first required to report the Freshmen On-Track Indicator to the Oregon Department of Education in the 2013/2014 school year. The ODE categorized a freshman "on-track" if the student was,

> "…part of the 9th grade cohort, enrolled at their district on the first school day in May, and who have earned 6 credits that count for their district's graduation requirements by the end of their first year of high school (Oregon Department of Education, 2017, p.1)."

The second independent predictor variable was "Total Days Absent Freshmen Year." This variable was operationalized as a continuous, numerical variable for the total number of days a student was absent their freshmen year.

Independent descriptive variables. The other five independent variables used in the study related to student demographics. Race/Ethnicity reflected the definitions used in the ODE database (White, Hispanic/Latino, Native Hawaiian/Pacific Islander, Black/African American, Multi-Racial, Asian, American Indian/Alaskan Native). Gender was coded as either male or female. The study used the ODE's "economically disadvantaged flag" for identifying a student's socioeconomic status. The ODE's economically disadvantaged flag indicated whether a student was eligible for a free or reduced lunch program. The study used the ODE's "Ever English Learner Flag" to identify Ever English learners (EEL). A relatively new term in Oregon, this flag indicated a student's participation in a program for non-native English speakers. A student who at any point in their public education career had been classified as an English Language Learner (ELL) or participated in an English for Speaker of Other Languages (ESOL) program was flagged as an Ever English Learner (EEL). The ODE's "Special Education Flag," was used to

identify special education students. This flag indicated a student's participation in an Individualized Education Plan (Oregon Department of Education, 2015).

Table 1

Independent Variables

	Operationalization	Research Question #
Freshmen On-Track Indicator	(Dichotomous) Student earned 6 credits freshmen year – Y. Student did not earn 6 credits freshmen year - N	RQ #1,3,4
Total Days Absent Freshmen Year	(Continuous) The numerical value of the total number of days a student was absent their freshmen year of high school.	RQ #2,3,4
Race/Ethnicity	(Dichotomous) Students classified as White were categorized in a group as "White". Students of Hispanic/Latino, Native Hawaiian/Pacific Islander, Black/African American, Multi-Racial, Asian, American Indian/Alaskan Native were classified as "Non-White".	RQ #3,4
Gender	(Dichotomous) Male = 0, Female = 1	RQ #3,4
Socioeconomic Status	(Dichotomous) Student received free or reduced lunch = Y. Student did not receive free or reduced lunch = N.	RQ #3,4
Ever English Learner	(Dichotomous) Student has received English as second language instruction = Y. Student has not received English as second language instruction = N.	RQ #3,4
Special Education Status	(Dichotomous) Student participated in an Individualized Education Plan = Y. Student did not participate in an Individualized Education Plan = N.	RQ #3,4

Dependent variable. EWS researchers have primarily utilized on-time, four-year graduation attainment as the dependent variable when determining the predictive validity of

independent variables (Allensworth & Easton, 2005; Bowers et al., 2013). For this study's dependent variable, students were categorized by "4 Year Graduation Status" as either "4 Year Graduate" or "Non-4 Year Graduate" based on the definitions found in the Oregon Department of Education's *Cohort Graduation Rate Policy and Technical Manual* (Oregon Department of Education, 2015) and *Dropout Rate & Exit Adjustment Policy and Technical Manual* (Oregon Department of Education, 2017). This study reflected the definitions and categorization of student outcomes that the Oregon Department of Education used to calculate public schools' four-year graduation rates at the time of publication.

For the cohorts of 2015-2018, the ODE categorized a student as a "4 Year Graduate" if within four years and one summer of entering high school, the student's outcome type was, "Regular High School Diploma" (exit code 4A), "Modified Diploma" (exit code 4A.b), "Modified High School Diploma" (exit code 4A.b), "Regular High School Diploma (Earned)" (exit code 4A), "Regular High School Diploma (Post Graduate Scholar)" (exit code 4F or 4G), or "Regular or Modified High School Diploma (Post Graduate Scholar)" (exit code 4F or 4G). In Oregon, each individual student receives only one exit code and therefore, students who received either exit code 4A, 4F 4G, or 4A.b were categorized as a "4-Year Graduate" in regards to the dependent variable.

Students were categorized as "Non-4-Year Graduate" if the student received an "Adult High School Diploma" (exit code 4B), an "Extended Diploma," a "GED" (exit code 4E), an "Alternative Certificate" (exit code 4C, 4D), or were "Continuing Enrollment" (exit code Category 1). Additionally, students classified as "Non-Complete/Dropouts Not Continuing Enrollment" were also categorized as "Non-4-Year Graduate." Oregon law defines "dropout" in ORS.339.505 as a student who, "(A) has enrolled for the current school year, or was enrolled in

the previous school year and did not attend during the current school year; (B) is not a high school graduate; (C) has not received a certificate for passing an approved high school equivalency test such as the General Educational Development (GED) test; and (D) has withdrawn from school (Oregon Department of Education, 2014).” Districts report students as dropouts using exit codes 3A (withdrew for personal or academic reasons), 3B (exceeded age requirement), 3C (removed for reasons other than health), 3D (enrolled in adult education), 3E (not enrolled – status unknown), 4B (adult high school diploma), 5E (withdrawn and under compulsory attendance age) depending on the individual circumstance. Therefore, students who received any of the following exit codes: 1A, 1B, 1C, 1D, 3A, 3B, 3C, 3D, 3E, 3F, 4B, 4C, 4D, 4E, 5A, 5D, 5E, 6B were categorized as “Non-4 Year Graduate” in regards to the dependent variable.

Finally, there was a third category of students that ODE removed from their four-year graduation calculations and who were also removed from this study’s sample. Students who were deceased or were permanently incapacitated (exit code 6A), had withdrawn due to long-term medical issues (exit code 5B), exchange students (exit code 5C), honorary diploma recipients, or students who had a documented transfer to outside the school district (exit codes 2A, 2B, 2C, 2D), were removed from the sample (Oregon Department of Education, 2015).

Table 2

Dependent Variable Graduation Outcomes

Exit Code	Name	Description	Dependent Variable Categorization
1A	Continuing Enrollment, Same School, Same District	Indicated students who were expected to continue in the same resident school within the same resident district.	Non-4 Year Graduate
1B	Continuing Enrollment, Different School, Same District	Indicated students who transferred to a different resident school within the same resident district.	Non-4 Year Graduate
1C	Continuing Educational Services in District but Not Assigned to a School	Indicated students who were expected to continue in the same resident district receiving educational services but were not assigned to a school.	Non-4 Year Graduate
1D	Continuing Enrollment in District, No School Information Available	Indicated students who were expected to continue in the same resident district, but no specific school information was available.	Non-4 Year Graduate
2A	Student Transferred to Another Public School District in Oregon	Indicated evidence had been received showing the student transferred to another public school district or public agency in the same state.	Removed from Sample
2B	Student Transferred to A Non-Public School in Oregon	Indicated students who were enrolled in a nonpublic K-12 school or setting in the same state.	Removed from Sample

2C	Student Transferred Outside of Oregon	Indicated students who transferred to a public or nonpublic school in another state or outside the United States.	Removed from Sample
2D	Student Transferred to a Non-Degree Granting Institution	This code indicated students who had transferred out of the school district into a non-degree granting district, school, or program that was not included in accountability reporting (i.e. Juvenile Detention Center)	Removed from Sample
3A	Withdrew for Personal or Academic Reasons	Students who withdrew for personal or academic reasons	Non-4 Year Graduate
3B	Exceeded Age Requirement	Students who exceeded age requirements, including any religious or cultural age limits recognized by state law or policy	Non-4 Year Graduate
3C	Removed For Reasons Other Than Health	Students who were removed from the education system for reasons other than health, and were not expected to return	Non-4 Year Graduate
3D	Enrolled in Adult Education	Students who enrolled in an adult education program, or some type of education program that did not lead to a diploma or other credential recognized by the state	Non-4 Year Graduate
3E	Not Enrolled – Status Unknown	Students who were not enrolled and their status was unknown (including students dropped	Non-4 Year Graduate

		from the rolls for excessive truancy)	
3F	Completed Prior School Year and Did not Re-Enroll as Expected	Students who did not re-enroll by October 1 as expected after completing the prior school year. Enrollment code 3F was only allowed after October, 1st the following school year	Non-4 Year Graduate
4A	4-Year Graduate	Indicated students who had completed an approved program of study, met all state or district requirements for a high school diploma, and were awarded a high school diploma. Student did not intend to participate in a post graduate scholars program	4 Year Graduate
4B	Completed Diploma-Track Program and Did Not Meet Requirements for HS Diploma	Indicated students who completed an approved program of study for high school completion, but did not meet all state or district requirements for a diploma	Non-4 Year Graduate
4C	Certificate of Achievement or Attendance	Indicated students who completed a program of study that did not address state diploma requirements and were awarded a certificate of achievement or attendance.	Non-4 Year Graduate
4D	CTE Certificate	Indicated students who completed a career and technical education program and earned a certificate recognized by the district.	Non-4 Year Graduate

4E	Equivalency Completion	Indicated students who passed an equivalency examination through an approved program, such as the GED.	Non-4 Year Graduate
4F	Initial Post Graduate Program	Indicated students who had completed all state and local requirements for graduation but had not been awarded a diploma due to pursuit of further education in the district.	4 Year Graduate
4G	Post Graduate Scholars Program	Indicated students who had completed an approved program of study, met all state or district requirements for a high school diploma, and who were awarded a high school diploma. Student qualified for and intend to participate in a Post Graduate Scholars program.	4 Year Graduate
5A	Withdrawn Due to Discipline or Eligibility	Indicated students who were not attending school for disciplinary or other eligibility reasons, but were eligible to enroll at a later date. These students were expected to return to school as some point.	Non-4 Year Graduate
5B	Long Term Medical Withdrawal	Indicated students who were not receiving services due to long term medical conditions but would be eligible to return to school upon completing a treatment program or recovery.	Removed from Sample
5C	Foreign Exchange Withdrawal	Indicated Oregon students who exited to participate in a foreign exchange program and are	Removed from Sample

		eligible to return to school in the United States.	
5D	Early College Admissions Withdrawal	Indicated students who exited the district and enroll in an early admission college program but were eligible to return to graduate.	Non-4 Year Graduate
5E	Withdrawn and Under Compulsory Attendance Age	Students were under the age for compulsory school attendance and withdrawn from school, but are eligible to return.	Non-4 Year Graduate
6A	Death or Permanent Incapacitation Withdrawal	Indicated students who died or were permanently incapacitated. Documentation was required.	Removed from sample
6B	Exceed Age Limits Withdrawal	Indicated students who had returned to school after receiving a completion credential or after they had reached the age until which the State guaranteed a free, appropriate public education, and had subsequently exited school.	Non-4 Year Graduate

Data Collection Procedures

The secondary student dataset for this study was stored primarily in the Oregon Department of Education's Achievement Data Insight (ADI) application. Student demographic, attendance, and academic data was collected and uploaded quarterly to the ODE ADI application by the Kentwood School District's data analyst, and was then validated by each individual school district before final certification by the ODE. For the 2015 and 2016 cohorts, the ODE

only required school districts to report school-level freshmen on-track data. Therefore, the individual student freshmen on-track status for the 2015 and 2016 cohorts was retrieved from the Kentwood School District's school information system archive. Similarly, the chronic absenteeism data for the 2015 cohort was also downloaded from the school information system archive because it was a not a required ODE district upload during the students' freshmen year.

Once approval for this dissertation proposal was granted and an IRB application (Appendix A) was approved, a formal request was made to the Kentwood School District's superintendent and data analyst for the 2015-2018 freshmen on-track, freshmen attendance, and demographic database files from the ODE ADI. Student data downloaded for this study was stored in a secure file on the researcher's computer that was password protected and will be deleted five years after the completion of the study.

Data Analysis Procedures

Multiple logistic regression is a common model of statistical analysis used in EWS research (Franklin & Trouard, 2016; Koon & Petscher, 2015; Stuit et al., 2016; Suh et al., 2007). Binomial logistic regression was an appropriate model for this study because the model calculated, "…the probability of being in a particular category of the dependent variable given the independent variables" (Laerd Statistics, 2015). To utilize binomial logistic regression, this study met the seven assumptions associated with the statistical analysis model. This study met the first two assumptions for a binomial logistic regression because there was one dependent variable that is dichotomous ("4-Year Graduate" vs. "Non-4-Year Graduate"), and one or more independent variables that were either continuous or nominal (Freshmen On-Track Status, Total Days Absent Freshmen Year, Gender, Race/Ethnicity, SPED Status, ELL Status, SES Status). The third assumption of binomial logistic regression was met because there was an independence

of options and mutual exclusivity among student placement within the dependent and independent variables. The fourth assumption of binomial logistic regression was that there are a minimum of 15 cases per each individual student variable (Laerd Statistics, 2015), which this study met.

Assumptions five, six, and seven related to how the data from the study fit the binomial logistic regression model and required specific tests that, among other options, were completed through SPSS. Assumption five sought out a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. The Box-Tidwell (1962) procedure and the binary logistic procedure within SPSS were used to test for this assumption (Laerd Statistics, 2015). Assumption six assumed no multicollinearity. SPSS reviewed correlation coefficients and Tolerance/VIF values to assure that two or more independent variables were not highly correlated with each other. Finally, assumption seven assumed no significant outliers, high leverage points or highly influential points. Casewise diagnostics within SPSS was used to detect outliers within the data set (Laerd Statistics, 2015).

The Omnibus Tests of Model Coefficients was used to determine the overall statistical significance of the model. The Hosmer and Lemeshow goodness of fit test was utilized to observe how poor the model was at predicting categorical outcomes. Finally, the Cox & Snell R Square and Nagelkerke R Square values was also analyzed to explain variance (Laerd Statistics, 2015).

The specificity and sensitivity of the early warning indicators was also analyzed. “Sensitivity” refers to, “…the percentage of cases that had the observed characteristic (“yes” for “Non-4 Year Graduate”) which were correctly predicted by the model (i.e., true positives) (Laerd Statistics, 2015).” Conversely, “Specificity” refers to, “…the percentage of cases that did not

have the observed characteristic ("no" for “4 Year Graduate”) and were also correctly predicted as not having the observed characteristic (i.e., true negatives) (Laerd Statistics, 2015).” These two measures are critical in interpreting the predictive validity of each early warning indicator.

Ideally, the EWS model would only flag students who actually dropped out as dropouts (true positives) and not flag students who graduated as dropouts (true negatives). Unfortunately, predictions models are imperfect and misidentifications can occur. This meant that sometimes, the EWS identified a student as a potential dropout who actually went on to graduate (false positive), as well as failing to flag students who actually dropped out as graduates (false negative). The more false positives and false negative that are inaccurately flagged or missed by the EWS, the less likely educational practitioners will value the identification capabilities of the model. Thresholds to balance both specificity and sensitivity were established to maximize the model’s true positive and true negative identifications and minimize false positive and false negative identifications.

Validity & Reliability

The internal validity threats related to instrumentation, selection, testing, maturation, statistical regression, and experimental mortality were minimal due to the nature of secondary data analysis. The primary threat to the external validity was the study’s use of a convenience sampling method. The decision to use this particular method was based on the need for rural school data as well as the relative ease of access to data from the Kentwood School District. Consequently, the study’s findings and results are highly contextualized. In addition, the generalizability of the results was limited as the data analysis was sourced from only one rural school district.

The threats to reliability of the study's findings were primarily based on the accuracy of the student data. The majority of the secondary student data was collected and stored in the district's school information system (SIS), validated by school-level and district-level employees, and finally audited and confirmed through the Oregon Department of Education processes, thus, the data was deemed reliable. Three data files, the 2015 cohorts' freshmen on-track status file, 2015 cohorts' freshmen total # of days absent file, and 2016 cohorts' freshmen on-track status file, were retrieved from the Kentwood School Districts' school information system archive because they were not required uploads by the ODE at the time. These files were reviewed by the district's data specialist to ensure accuracy and consistency with the broader data set.

Limitations

The foremost limitation of this study was related to the specificity of the study's sample. Although the sample was chosen with intentionality to observe the predictive validity of specific variables within a rural setting, the relatively small, rural samples certainly limited the generalizability of the study's findings. Likewise, the specific operationalization of the dependent variable was another limitation of the study. While this study, along with the majority of EWS research defined a "high-school graduate" as an 4-year, on-time, diploma recipient (Allensworth & Easton, 2005; Bowers et al., 2013), there were other categories of students who could have been defined as "4-Year Graduates." Expanding the definition of "high-school graduate" to include students who received GEDs, graduated in 5 years, or received an adult high school diploma would have changed the results of the study relating to the dependent variable. Choosing to use the ODE rules for calculating graduation rates certainly had a substantial impact on this study's findings. The decision to implement the ODE's 2017-2018 guidelines for

classifying students as either a "4-Year Graduate" or "Non-4 Year Graduate" was based on the desire to have the graduation classification match the context of study's sample. Using these guidelines allows for the Kentwood School District stakeholders to interpret the results within the same guidelines that are utilized throughout the state of Oregon.

Research Ethics

I served in two different positions within the Kentwood School District over the course of this research study. My initial role within the district was Assistant Principal of Curriculum at the district's comprehensive high school. In this position, I was primarily responsible for teacher evaluations and creating/monitoring systems to improve student achievement. The second role that I held within the Kentwood School District was Director of School Improvement at the school district's central office. In this role, I primarily worked with the district's superintendent, school board, building administrators, and other stakeholders on various school improvement initiatives and projects aimed at increasing student achievement K-12.

As a result of my different roles within the Kentwood School District, I had either interacted with, or was familiar with, the vast majority of students whose secondary data was analyzed in this study. To maintain student confidentiality and ensure ethical data collection procedures, I put several safeguards into place. The first step in protecting students' confidential information was to use the pseudonym "Kentwood School District" rather than the actual name of the school. Although simplistic, this step provideed the first line of defense in protecting student confidentiality. Furthermore, all student data for this research study was retrieved and reviewed by the district's Data Specialist prior to data analysis. This additional precaution helped ensure the accuracy of the study's data, as well as provided a further layer of objectivity to the data collection process. As required, IRB approval was also secured through George Fox

University prior to conducting research. In addition, prior to the data analysis, all student names were de-identified to further protect participant confidentiality.

Since my role as the Kentwood School District's Director of School Improvement provided an opportunity to work with a variety of stakeholders on issues directly related to this study, a number of precautions were taken and will continue to be implemented in order to prevent unintentional or inadvertent misinterpretation and use of the study's findings. One primary step to prevent misrepresentation of the study's findings is to always present the study in context of the larger findings of the EWS research field. Presenting and discussing this study's results as a very small piece of a much larger body of EWS research demonstrates the importance of not making imprudent decisions or actions based on a singular study or finding. Furthermore, the study's findings will always be presented and discussed with a disclaimer regarding the dangers that exist with forecasting and predicting potential the likelihood that a student will drop out. As discussed in the literature review, while EWS can help districts flag students who may show signs of being at-risk of dropping out, there always may be false positives and false negatives and it is crucial that EWS are used to provide additional support for at-risk students rather than an excuse to give up on a student.

Although participants were de-identified, demographic data regarding race/ethnicity, gender, socioeconomic status, special education status, and Ever English Learner status was incorporated into the secondary data analysis. The analysis of demographic characteristics was crucial for identifying trends and themes in the data, but did have the potential to lead to ethical issues if communicated or interpreted erroneously.

Although there always remains a chance that a study's results will be misused or misinterpreted, these precautionary measures meant there was minimal risks for negative

consequences for the Kentwood School District and the individual students whose secondary data was analyzed in this study.

Chapter Four

Results

The purpose of this study was to investigate and analyze the extent to which high school freshmen credit attainment and freshmen absenteeism could serve as predictors of four-year graduation attainment within a rural, Oregon school district. Student data from the Kentwood School District's 2015, 2016, 2017, and 2018 cohorts were analyzed to determine the predictive validity of the two independent variables. Both predictors, or independent variables, have been identified in the education research literature as having a correlation with four-year graduation attainment (Allensworth, 2013; Bruce et al., 2011). As is common in logistic regression (LR) studies, covariates were also included to examine any moderating effects of the independent variables on the dependent variables. The covariate variables in this study were gender, race/ethnicity, socioeconomic status, special education status, and English learner status. Thus, a total of eight variables were included in the analysis. Data were downloaded from the Oregon Department of Education's *Achievement Data Insight Application* and the Kentwood School District's *Student Information System Archive*. Data were imported into Excel and then uploaded into IBM SPSS Statistics 25 for statistical analysis.

Description of Sample

The overall 2015, 2016, 2017, and 2018 cohorts from the Kentwood School District contained a total of 764 students with complete data for this study's eight unique variables. Students' data was considered complete if information was available for each independent variable as well as the dependent variable. Of the 764 students with complete data, 33 of those students had an exit outcome as "transfer." Students with an exit outcome of "transfer" were removed from the sample because their outcome as either a "4-Year Graduate" or "Non-4 Year

Graduate" was unknown. With the transfer students' data removed from the sample, the data of 731 students was analyzed. The demographic breakdown (sex, race/ethnicity, disability status, ever English learners, SES) of the sample is provided in Table 3.

One adjustment was made in the categorization of students' race/ethnicity classification to meet the assumptions of binomial logistic regression. The race/ethnicity of students was consolidated into two groups ("White" and "Non-White") to provide the minimum 15 cases per group required of binomial logistic regression. The students who were identified as American Indian/Alaska Native (n=18), Asian (n=1), Black/African American (n=1), Hispanic/Latino (n=107), Multi-Racial (n=44) were thus classified together as "Non-White" (n=171). Although some independent groups had the minimum n=15 cases (e.g. Hispanic/Latino and Multi-racial categories), there was no substantive theoretical reason one way or the other to distinguish these from the other race/ethnicities into a separate 'Other' category. In this case, with very low cell sample sizes for several categories, it is arguable that the power to detect effects is increased with the larger combined cell sample size for all groups that are 'Non-White.'

Table 3

Demographic Variables Frequencies

	Frequency	Percent (%)
Sex		
Female	346	47.3
Male	385	53.7
Race/Ethnicity		
White	560	69.6
Non-White	171	23.4
Students with Disabilities		
Yes	114	15.6
No	617	84.4
Ever English Learner		
Yes	47	6.4
No	684	93.6
Economically Disadvantaged		
Yes	482	65.9
No	249	34.1

Independent Variables

This study analyzed two different independent predictor variables that were measurements from students' freshmen year. The first independent variable was called "freshmen on-track status" and was a dichotomous variable measuring whether a student had (Y =1) or had not (N=0) earned a total of six credits by the start of their sophomore year. Over the four cohorts, 78.9% of the study's students earned the necessary credits to be considered on-track to graduate after their freshmen year. The complete distribution for the freshmen on-track variable is found in table 4.

The second independent variable that was analyzed was, "total # of days absent freshmen year". The data was analyzed as a continuous numerical variable that reflected the total number of days the student was coded as absent during their freshmen year. The distribution of this variable is shown in table 4, as well.

Table 4

Independent Variable Frequencies

	Frequency	Percent (%)
Freshmen on Track Flag		
Yes	577	78.9
No	154	21.1
Total # of Days Absent Freshmen Year		
0 - 3.5	221	30.2
4 - 7.5	180	24.6
8 - 11.5	110	15.1
12 - 15.5	71	9.7
16 - 19.5	57	7.8
20 +	92	12.6

Dependent Variable

The dependent variable for the study was a dichotomous measurement of students' 4-year, on-time graduation status. Students were classified as either "4-Year Graduate" or "Non-4 Year Graduate" based on their exit code. Students were considered a "4-Year Graduate" if they had a recorded outcome type that was either, "Regular High School Diploma" (exit code 4A), "Modified High School Diploma" (exit code 4A.b), "Regular High School Diploma (Earned)" (exit code 4A), "Regular High School Diploma (Post Graduate Scholar)" (exit code 4F or 4G), or "Regular or Modified High School Diploma (Post Graduate Scholar)" (exit code 4F or 4G). Conversely, students were categorized as a "Non-4 Year Graduate" if their outcome type was, an "Extended Diploma", a "GED" (exit code 4E), or were "Continuing Enrollment" (exit code Category 1). Furthermore, students classified as "Non-Complete/Dropouts Not Continuing Enrollment" were also categorized as "Non-4 Year Graduate." The graduate sample size was equal to x students and the non-graduate sample size was equal to 146 students, over the four cohorts.

Table 5

Dependent Variable Frequencies

	Frequency	Percent (%)
4-Year Graduate		
Regular High School Diploma	496	67.8
Modified High School Diploma	27	3.6
Regular High School Diploma (Earned)	43	5.8
Regular High School Diploma (Post Graduate Scholar)	14	1.9
Regular or Modified High School Diploma (Post Graduate Scholar)	5	0.6
Non-4 Year Graduate		
Extended Diploma	3	0.4
GED	30	4.1
Continuing Enrollment	31	4.2
Non-Complete/Dropouts Not Continuing Enrollment	82	11.2

Analysis

Binomial logistic regression was used to analyze the data set for two primary functions. First, the statistical analysis determined if any of the independent variables had a statistically significant effect on the dependent variable. Second, the analysis explained how well the logistic model predicted the dependent variable (Laerd Statistics, 2015). For this type of analysis, SPSS first analyzed the model with only the constant and no independent variables added. Table 5 below demonstrates the model’s predictions with no independent variables added, and all students simply classified as “4-Year Graduate”. By predicting that all 731 students were” 4-Year Graduates”, the model was 80% accurate.

Table 6

Step 0 Classification Table

		Model Predictions		
Step 0		Predicted 4-Year Graduate	Predicted Non-4 Year Graduate	Percentage Correct (%)
	Observed 4-Year Graduate	585	0	100.0
	Observed Non-4 Year Graduate	146	0	0
	Overall Percentage			80.0

Note: a. Constant is included in the model. b. The cut value is .500

After determining the model's accuracy without independent variables, the Omnibus Test of Model Coefficients was utilized to demonstrate the overall statistical significance of the model. This test provides insight regarding how well the model predicts the dependent variable without independent variables. As seen in table 7, the Chi-square value was 220.190 and the model was statistically significant at $p < .0005$.

Table 7

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	220.190	7	0.000
	Block	220.190	7	0.000
	Model	220.190	7	0.000

The Hosmer and Lemeshow Goodness of Fit Test was used to analyze how poorly the model predicted categorical outcomes (Laerd Statistics, 2015). In other words, this test helps to analyze how well the model was able to predict outcomes compared to the actual observed outcomes. If a substantial portion of the predicted outcomes do not align with the observed outcomes, the model is essentially worthless. For this particular test, the model had a Chi-square value of 2.74 and was not statistically significant ($p = .949$), which indicated that the model was not a poor fit.

The Cox & Snell R^2 and Nagelkerke R^2 values from the Model Summary were utilized to better understand the amount of variance in the dependent variable that could be explained by the model (Laerd Statistics, 2015). According to the Model Summary, the explained variation in the dependent variables ranged from 26% according to the Cox & Snell R^2 Square, and 41% according to the Nagelkerke R^2. Additionally, the -2 Log Likelihood value was 510.843[a]. The change in log-likelihood indicates the amount of variance that is explained by the new model. When comparing different study outcomes of the same substantive problem, the -2 Log Likelihood values can be effectively used to compare the extent to which a particular model explains the variance within the overall model.

Category prediction. After determining the fit of the model, binomial logistical regression was used to predict the probability that a student would be classified as either a "4-Year Graduate" or "Non-4 Year Graduate" based on a student's independent variables. As previously seen in table 6, which did not include any independent variables, the model accurately predicted 80% of student outcomes without incorporating independent variables. The percentage accuracy in classification increased to 84.5% when incorporating the independent variables into the model (see Table 8). This increase in correct classification signifies that 4.5% of the observed variance in the model can be attributed to the independent variables (Laerd Statistics, 2015).

Table 8

Step 1 Classification Table

	Model Predictions		
Step 1	Predicted 4-Year Graduate	Predicted Non-4 Year Graduate	Percentage Correct (%)
Observed 4-Year Graduate	551	34	94.2
Observed Non-4 Year Graduate	79	67	45.9
Overall Percentage			84.5

Note: The cut value is .500

Sensitivity and specificity. Table 8 also demonstrates the sensitivity and specificity of the model. The sensitivity of the model, which is the percentage of the cases that had the observed characteristics, “Non-4 Year Graduate”, and were correctly predicted by the model as a “Non-4 Year Graduate” was 45.9%. Sensitivity and specificity in logistic regression analysis are colloquially categorized as either “true positive,” “true negative,” “false positive,” or “false negative”. In this regard, the particular figure represents the percentage of “true positives” predicted by the model.

Table 9

Classification Correct Table

	n	% Classification Correct
Correctly Predicted 4-Year Non-Graduate	67	45.9%
Correctly Predicted 4-Year Graduate	551	94.2%
Correctly Predicted Overall	618	84.5%

The specificity of the model is measured by the percentage of cases that did not have the observed characteristic – i.e., those classified as “Non-4 Year Graduate” – and were correctly predicted as not having the observed characteristic (Laerd Statistic, 2015). In other words, this metric represents the percentage of “4-Year Graduate” that the model was able to correctly predict. This measurement is also referred to as the percentage of true negatives. For this

measure, the model correctly identified 551 students as “4-Year Graduate”. The specificity of the model for true negatives equaled 94.2%.

False negatives and false positives were also assessed within the model. The false negatives in this case were students that the model predicted to be “4-Year Graduates” but, in reality, were “Non-4 Year Graduates”. The false negative percentage was 54.1%. The false positives in this model were students who were predicted to be “Non-4 Year Graduates” but, in fact were “4-Year Graduates”. The false positive percentage was a mere 5.8%.

SPSS also provides results for the model’s positive predictive value. This value is “the percentage of correctly predicted cases with the observed characteristic compared to the total number of cases predicted as having the characteristic” (Laerd Statistics, 2015). For this model, 66.3% of all predicted non-graduates were accurately predicted by the model.

Conversely, the negative predictive value explains the percentage of correctly predicted cases without the observed characteristic compared to the total number of cases predicted as not having the characteristic (Laerd Statistics, 2015). For this model, 87% of the students were correctly predicted as four-year graduates.

Variables in the equation. The contribution and statistical significance of each independent variable to the overall model was established to determine which variables had the greatest impact on predicting the dependent variable. The Wald test statistic was utilized to identify the statistical significance of each of the independent variables. Results from the Wald test (column “Wald”) and the statistical significance of each independent variable (column “Sig”) are listed in Table 10. Of the seven combined independent variables and covariates, three were found to be statistically significant predictors of 4-year graduation status: total # of days

absent (p < .005), freshmen on track status (p < .005), and economically disadvantaged status (p < .005).

In addition to the statistical significance of each independent variable, SPSS incorporated the *B* coefficients (column “B”) into the equation to predict the probability of an event (i.e. “Non-4 Year Graduate” or “4 Year Graduate”) occurring. The coefficients help to explain the “change in the log odds that occur for a one-unit change in an independent variable when all other independent variables are kept constant” (Laerd Statistics, 2015). In order to help the interpretation of *B* coefficients, SPSS also includes the odds ratios for each independent variable within the “Exp(B)” column. In other words, this column explains the increase in the odds that a student will be a non-4-year graduate, based on a one-unit change in the independent variable. Note that dummy groupings were unnecessary because none of the covariates had more than two categories. These results were vital for answering the four research questions of the study.

Table 10

Variables in the Equation

Variables	B	S.E.	Wald	Sig	Exp(B)
Total # of Days Absent	0.054	0.011	23.368	0.000	1.056
Freshmen on Track	-2.004	0.249	64.744	0.000	0.135
Students with Disabilities	0.310	0.287	1.163	0.281	1.363
Ever English Learner	-0.895	0.548	2.662	0.103	0.409
Economically Disadvantaged	1.450	0.337	18.535	0.000	4.262
Gender	-0.341	0.233	2.149	0.143	0.711
Race/Ethnicity	-0.148	0.293	0.255	0.614	0.862

Note: Variable(s) entered on step 1: # of Days Absent, Fresh On Track Binary, SWD Binary, EEL Binary, Economical Disadvantaged Binary, Recoded Gender, Recoded Race/Ethnicity.

Research question #1. To what extent did the freshmen on-track indicator status predict the probability that a student graduated within four years?

The *B* coefficient for the dichotomous “Freshmen On Track” independent variable equaled -2.004 with an odds ratio Exp(B) of 0.135. An Exp(B) value less than 1.000 indicates a

decrease in odds for the dependent variable in relation to an increase in one unit of the independent variable. For this study, since “Freshmen On Track - Y” was equal to 1 and “Freshmen On Track – N” was equal to 0, the Exp(B) value needed to be inverted. To invert the Exp(B) value, the Exp(B) value “0.135” was divided by 1 to obtain the value 7.407. With the inversion, the Exp(B) for the freshmen on track independent variable was equal to 7.407. This result indicates that students who were not “on-track” at the beginning of their sophomore year were 7.407 times more likely to be a “Non-4 Year Graduate.” The Wald test found this independent variable to be statistically significant at $p < .005$.

Research question #2. To what extent did the total number of days a student was absent their freshmen year predict the probability that the student graduated within four years?

The *B* coefficient for the continuous “Total # of Days Absent” independent variable equaled 0.054. The odds ratio, Exp(B), for this particular variable was 1.056. This value indicates that for every day that a student was absent their freshmen year, the log odds that they would be classified as a “Non-4 Year Graduate” increased by 1.056. The Wald test also established this variable to be statistically significant at $p < .005$.

Research question #3. To what extent did combining a student’s freshmen on-track indicator status and total number of days absent their freshmen year, predict the probability that the student graduated within four years?

The model found that both the “freshmen on track” and “total # of days absent” independent variables were statistically significant at the $p < .005$ level. With the “freshmen on-track” Exp(B) value equal to 7.407 and the “total # of days absent” Exp(B) value equal to 1.056, these two measures proved to have high predictive validity for a student’s graduation status.

Research question #4. To what extent did the freshmen on track indicator status, total number of days a student was absent their freshmen year, and demographic variables (gender, race/ethnicity, SPED, LEP, and SES) predict the probability of four-year graduation attainment?

Focusing exclusively on the variables that had statistically significant contribution to the model, three conclusions can be established regarding research question #4. Economically disadvantaged students had 4.262 times higher log odds to be classified as a Non 4 Year Graduate than students that were not economically disadvantaged. Students that were “off-track” to graduate at the beginning of their sophomore year were 7.407 times more likely to not graduate than those that were “on-track”. Finally, the change in odds that students would be a “Non-4 Year Graduate” increased by 1.056 with each day the student was absent. In other words, the log odds that a student would drop out rose slightly with each day the student was absent their freshmen year. The demographic variables of gender ($p=.143$), race/ethnicity ($p=.614$), Ever English Learner status ($p=1.03$), and SWD status ($p=.281$) were shown by the model to be non-statistically significant predictors at the $p < .005$ level. Therefore, the model can establish that students who were off-track after their freshmen year, had significant absenteeism, and were economically disadvantaged certainly had a higher likelihood to be a Non-4 Year Graduate than those students who do not have those characteristics.

Assumptions

The seven assumptions of Binomial Logistic Regression were met and tested for within SPSS. Assumption one of the statistical model was met through the study’s one dependent variable that was dichotomous (“4-Year Graduate” vs. “Not 4-Year Graduate”). The second assumption was met through the study’s independent variables that were either continuous or nominal (Freshmen On Track Status, Total Days Absent Freshmen Year, Gender,

Race/Ethnicity, SPED Status, ELL Status, SES Status). The independence of options and mutual exclusivity among student placement within the dependent and independent variables fulfilled the third assumption of binomial logistic regression. The fourth assumption was met as all student subgroups contained more than 15 cases. By combining the race/ethnicity independent variable into “White” and “Non-White”, the smallest subgroup in the study was Ever English Learners at n=47 students.

Assumption five of binomial logistic regression ensures a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. The Box-Tidwell (1962) procedure and the binary logistic procedure within SPSS were used to test for this assumption (Laerd Statistics, 2015). The sixth assumption was that no multicollinearity existed among the study’s variables. SPSS assessed correlation coefficients and Tolerance/VIF values to assure two or more independent variables were not highly correlated with each other (Laerd Statistics, 2015). The final assumption of binomial logistic regression assumes that no significant outliers exist in the sample. To meet this assumption, Casewise diagnostics were used to assure no significant outliers in the data set.

Conclusion

The binomial logistic regression model in this study identified two independent variables and one covariate that were statistically significant predictors of a student’s odds of becoming a non-graduate. One statistically significant independent variable from this study was the total number of days a student was absent their freshmen year. This study’s findings regarding freshmen absenteeism affirm the conclusion that the more days a student is absent their freshmen year, the higher the odds that the student will not graduate. Additionally, the impacts of freshmen on track variable was also a statistically significant finding from this study. The statistical

analysis determined that students in the Kentwood School District who did not earn six or more credits their freshmen year were significantly less likely to be a four-year graduate than a student who did earn six credits their freshmen year. Finally, the economically disadvantaged variable was determined to be statistically significant. This result signifies that if a student participated in a free or reduced lunch program, that student had greater than average odds of becoming a non-graduate.

Chapter Five

Discussion and Conclusions

The purpose of this research study was to analyze and evaluate the extent to which high school freshmen credit attainment, freshmen absenteeism, and demographic covariates could serve as early warning indicators of four-year graduation attainment within a rural, Oregon school district. A better understanding of the role that these variables play in identifying at-risk students potentially enables the Kentwood School District to target resources and supports to the students in most need of intervention. With this is mind, the predictive validity of these independent variables and covariates were analyzed using binomial logistic regression. While the majority of EWS research has been conducted among urban and suburban student populations, the results from this particular study with rural students affirmed a number of the findings of the broader EWS research field, while also providing practical significance for the Kentwood School District. Although this study had several limitations, the study's findings nevertheless hold several pragmatic applications within their local context.

Discussion of Findings

There were four primary research questions addressed through this study. All four questions related to the extent to which specific independent variables and covariates could predict the probability of students' on-time graduation attainment. Additionally, the four research questions all had statistically significant findings.

Research question #1. To what extent did the freshmen on-track indicator status predict the probability that a student graduated within four years?

For this study, the freshmen on-track indicator was defined as whether or not a student earned a total of six credits by the beginning of their sophomore year. A student who had earned

a total of six credits in any subject was classified as “on-track” and a student who had earned less than six credits was considered “off-track”. For the students in the Kentwood school district cohorts of 2015, 2016, 2017, and 2018, this measure proved to be a highly predictive early warning indicator.

This study’s statistical analysis determined that students who were classified as “off-track” after their freshmen year were nearly seven times more likely to be a non-graduate than students who were categorized as “on-track”. Of all the variables and covariates analyzed in this study, the freshmen on-track indicator had the highest predictive validity for graduation attainment. The results from this study regarding the predictive capabilities of the freshmen on-track indicator affirmed the findings of a number of key researchers and studies within the broader EWS field (Allensworth & Easton, 2005; Allensworth & Easton, 2007; Dalton, Glennie, & Ingels, 2009; Johnson & Semmelroth, 2010).

Allensworth and Easton (2005) conducted the preeminent study regarding the freshmen on-track indicator as a predictor of high school graduation through analyzing 23,000 students in the Chicago Public School system. The researchers found that 81% of their sample that were on-track at the end of freshman year graduated from high school on time (Allensworth & Easton, 2005). Interestingly, the statistical analysis from the Kentwood School District cohorts had an even higher percentage of on-track students graduating within four years. For this study’s sample, 90% of Kentwood School District students that were on-track after their freshmen year went on to graduate on time. Conversely, only 40% of students that were off-track after their freshmen year earned enough credits to graduate within four years.

With the findings of this study, along with the larger body of EWS research, it can be concluded that the total number of credits that a student earns their freshmen year within the

Kentwood School District is a major signal as to whether or not that student will graduate within four years. Additionally, these results affirm the predictive validity of the freshmen on-track indicator as an early warning indicator, not only for students in urban and suburban students seen in the majority of EWS research, but also for the rural students in the Kentwood School District.

Research question #2. To what extent did the total number of days a student was absent their freshmen year predict the probability that the student graduated within four years?

The EWS research field has established high absenteeism during a student's freshmen year as an early warning indicator for potential non-graduates (Allensworth & Easton, 2005; Burke, 2015; Mac Iver & Messel, 2013). The results from this study regarding freshmen absenteeism were statistically significant and aligned with the findings of the broader field of research. For the Kentwood School District 2015-2018 cohorts, the odds that a student would be a non-graduate increased with each day that the student was absent their freshmen year.

In Oregon, chronic absenteeism is defined as a student who was absent for 10% or more of the total possible days in a school year. As a typical school year in the Kentwood School District consists of 170 student contact days, students who missed 17 or more days are deemed "chronically absent". For the cohorts of 2015-2018, only 51% of students who were chronically absent their freshmen year graduated on time. Although the graduation rates of chronically absent freshmen students in the Kentwood School District were higher than those found in larger EWS research studies, the results from this study affirm the finding that chronic absenteeism freshmen year is tied to lower than average graduation rates. For example, in Allensworth and Easton (2007) study, only 21% of students who missed more than fifteen days of their freshmen year graduated on time. Similarly, Burke (2015) concluded that 83% of freshmen students with attendance rates lower than 80% did not graduate on time.

Research question #3. To what extent did combining a student's freshmen on-track indicator status and total number of days absent their freshmen year, predict the probability that the student graduated within four years?

While identifying at-risk students through a single early warning indicator can provide statistically significant results, combining multiple independent variables increases the predictive validity of EWS models (Balfanz et al., 2007; Gleason & Dynarski, 2002; Suh et al., 2007). For this study, both the freshmen on-track indicator and total number of days a student was absent their freshmen year proved to be statistically significant predictors of on-time graduation attainment. Coinciding with the findings from the field, these two independent variables provided a strong indication of whether or not a student would graduate among the Kentwood School District 2015-2018 cohorts. Students who failed to earn six credits before the start of their sophomore year were seven times more likely to be a non-graduate and the probability that a student would not graduate on-time increased with each day they were absent their freshmen year. For this study's sample, only 34% of students who were both off-track and absent 10% or more of their freshmen year graduated on-time. These two student variables were statistically significant indicators of graduation status and provide justification for increasing the level of support and intervention for students who meet both early warning indicators.

Research question #4. To what extent did the freshmen on track indicator status, total number of days a student was absent their freshmen year, and demographic variables (gender, race/ethnicity, SPED, LEP, and SES) predict the probability of four-year graduation attainment?

Affirming the conclusions of the broader EWS research literature, this study found that the freshmen on-track indicator and the total number of days a student was absent their freshmen year had high predictive validity for graduation attainment within the Kentwood School District.

In addition to these two independent variables, this study also examined the predictive validity of several demographic variables (gender, race/ethnicity, SPED, EEL, and SES).

The covariate demographic variables in this study were more varied in their predictive validity regarding graduation attainment. For the Kentwood School District 2015-2018 cohorts, race/ethnicity, gender, Ever English Learner status, and disability status were not found to have a statistically significant bearing on whether or not a student would graduate within four years. Although likely due to the study's small sample size, these findings were in slight contrast to the findings of the larger EWS field. While a number of researchers have found that females had a slightly higher graduation rate than males (Burke, 2015; Dalton et al., 2009; Roderick, 1993; Soland, 2013; Uekawa et al., 2010), the graduation rates for both males and females in this study were both equal to 80%. Similarly, the EWS research literature has demonstrated that SPED-identified students had a higher likelihood of non-graduation (Balfanz et al., 2007; Burke, 2015; Uekawa et al., 2010). Although this study found that the SPED-identified students had a lower graduation rate (68%) compared to non-SPED-identified students (82%), the findings were not statistically significant. Finally, students identified as English language learners (ELL) or having limited English proficiency (LEP) have also been found to have higher dropout rates (Allensworth & Easton, 2012; Balfanz et al., 2007; Saunders et al., 2008). For the Kentwood School District 2015-2018 cohorts, Ever English Learners had an on-time graduation rate of 85% but these results were not considered statistically significant.

In regards to race/ethnicity, researchers have established differences in graduation rates with higher than average rates observed among Asian populations (Burke, 2015; Hess et al., 1985; Neild & Balfanz, 2006; Uekawa et al., 2010) and lower than average rates observed in African American, Latino, and Native American populations (Burke, 2015; Dalton et al., 2009;

Neild & Balfanz, 2006; Saunders et al., 2008; Uekawa et al., 2010). Due to the sample size requirements of binomial logistic regression, the race/ethnicity groups from the Kentwood School District 2015-2018 cohorts were consolidated into “whites” and “non-whites”. For this study, the difference in graduation attainment between “whites” and “non-whites” was not found to be statistically significant.

One demographic variable that proved to be a statically significant early warning indicator of graduation attainment when holding all other variables constant was students’ socioeconomic status. For this study, students’ socioeconomic status was categorized by whether or not a student participated in a free/reduced lunch program. Students who received free/reduced lunch were deemed “economically disadvantaged.” The educational research has repeatedly demonstrated lower-than-average graduation rates for economically disadvantaged students (Dalton et al., 2009; Ensminger & Slusarcick, 1992a; Franklin & Trouard, 2016; Hernandez, 2011; Paasch & Swaim, 1993; Saunders et al., 2008; Suh et al., 2007). This study’s findings regarding the graduation attainment of economically disadvantaged students was consistent with the larger body of educational research. Students identified as economically disadvantaged within the Kentwood School District’s 2015-2018 cohorts were over four times as likely to not graduate compared to their non-economically disadvantaged peers. Only 350 out of the 482 (73%) students identified as economically disadvantaged in the Kentwood School District graduated on time compared to 235 out of 249 (94%) students who were not identified as economically disadvantaged. The vastly differing graduation rates between economically disadvantaged students and non-economically disadvantaged students certainly affirms the importance of socioeconomic status as an early warning indicator.

Within the Kentwood School District 2015-2018 cohorts, a student's freshmen on-track status, socioeconomic status, and total number of days absent freshmen year all played a statistically significant role in whether or not the student would graduate on time. Demographic variables such as gender, race/ethnicity, SPED status, and ever English learner status proved to not be statistically significant factors regarding on time graduation attainment. While the clear majority of EWS research has been conducted among urban and suburban student populations (Allensworth, 2013; Allensworth & Easton, 2007; Bowers, 2010; Mac Iver & Messel, 2013; Neild, Balfanz, & Herzog, 2007), a number of these findings from this study's rural student sample are aligned with the larger body of EWS research findings.

Limitations

Although this study yielded a few statistically significant results, the structure, sample, and statistical analysis of the study revealed several limitations to the findings. While the study's practical applications for the Kentwood School district are clear, the limitations of the study impacted both the findings and generalizability of the results.

The foremost limitation of the study relates to the small sample size. Small Ns impact the generalizability of a study's findings. More importantly, the convenience of the sampling procedure with lack of randomized selection severely limits external validity. While utilizing local data from a single school district can help to provide contextualized practical applications and account for unique variations in state and local reporting and academic requirements (Bowers et al., 2013; Neild & Balfanz, 2006; Paasch & Swaim, 1993; Pinkus, 2008; Strange, 2011; Stuit et al., 2016), having this study's sample sourced from a single, rural school district dramatically impacted the generalizability of the study's findings. Additionally, the study's sample only spanned four years of cohorts from the Kentwood School District. The relatively

small timeframe leaves the findings prone to contextualized factors that may have impacted the results. The potential impact of localized influences on the student data certainly influence the generalizability of the study's finding.

Another validity limitation to the study was the sample size requirements necessary for the study's statistical analysis. The sample size requirements for binomial logistical regression necessitated the consolidation of all minority race/ethnicity students to be grouped into a single category "non-white". This necessary step prohibited identifying detailed themes between different race/ethnicity groups as well as further limited the generalizability to a broader context.

In addition to this study's limitations regarding generalizability, another limitation of the study was the necessity to have complete longitudinal data for each student to be included in the sample. Given that the data for the study was sourced from a single school district, a student that transferred in or out of the Kentwood School District after their freshmen year without complete data was excluded from the sample. The exclusion of students with missing data certainly may have influenced the study's findings. The issue of student mobility is a common limitation of EWS research since "student mobility" is in itself an established early warning indicator within the field (Jimerson et al., 2000; South, Haynie, & Bose, 2007). The impact of excluding students with missing data who transferred in or out of the Kentwood School District after their freshmen year cannot be overstated since mobile students are more than twice as likely to dropout compared to their non-mobile peers (South et al., 2007). Incorporating these students into the data may have adversely impacted the study's findings.

This study was also limited in the number of variables analyzed for their predictive validity for graduation attainment. The EWS field has explored a vast array of student variables for their correlation to on-time graduation (Bowers et al., 2013). Due to limits in consistent and

accurate longitudinal data in both the Kentwood School District and State of Oregon, this study exclusively analyzed the freshmen on-track indicator and freshmen absenteeism along with demographic covariates. These constraints certainly limited the number of early warning indicators that were assessed for this particular sample.

Another limitations of this study was the manner in which students' socioeconomic status was measured. Aligned with the Oregon Department of Education definitions, student socioeconomic status was determined by whether or not they had participated in a free/reduced lunch program. Although this was the most convenient method for this particular study, there are many other ways to measure socioeconomic status. Metrics such as parental income, total household income, or family tax bracket are all common ways to operationalize socioeconomic status. This study's use of free/reduced lunch status as the metric for students' socioeconomic status may have influenced the results for that variable.

One final limitation of this study was related to the follow up statistical analysis procedures after the completion of the binomial logistic regression. An emerging statistical practice within the EWS field is the use of Receiver Operating Characteristic (ROC) plots. The ROC analysis allows the model to, "…consider all possible cut-off points in your data, and how each cut-off point changes the specificity and sensitivity of the test" (Laerd Statistics, 2015). In other words, ROC analysis helps to evaluate the accuracy and thresholds of specific independent variables (Bowers et al., 2013; Gleason & Dynarski, 2002). The absence of a ROC analysis limits the study's findings regarding the cut-off points for the potential specificity and sensitivity of the model.

Recommendations for Practice

The findings from this study foster a number of practical recommendations for the Kentwood School District. As each student has a unique set of needs, policy makers should provide additional resources that take on a variety of forms in order to adequately support the distinct social, emotional, academic, and practical necessities of each student. Based on the findings of this study, the additional resources should target students that are either off-track for graduation, economically disadvantaged, or demonstrating high levels of absenteeism.

For students that are off-track after their freshmen year, the school district could use this study's findings as justification to further develop credit recovery options for off-track freshmen students. Additionally, the findings from this study as well as the larger research field, provide sound evidence for a continued focus on intervention and support for chronically absent freshmen students within the Kentwood School District. Finally, due to the lower-than-average graduation rates for economically disadvantaged students, policy makers may consider allocating additional resources to support the district's economically disadvantaged students. Ultimately, it is recommended that policy makers within the Kentwood School District ensure that each student who is flagged as at-risk is placed within a broader, systematic support network that accommodates the student's individualized needs.

Suggestions for Further Research

This study presented several opportunities and considerations for further research. Although the study provided practical implications for the Kentwood School District, a few future actions could help increase generalizability, provide more comprehensive statistical analysis, account for student mobility, and assess the predictive validity of a broader range of early warning indicators.

To increase the generalizability of the study, several strategies could be implemented. One suggestion for future study is to incorporate the student cohorts from rural school districts with similar student demographics from across the county. While this study sought to explore the predictive validity of early warning indicators for a highly contextualized rural sample, incorporating secondary data from various rural districts across the country would greatly increase the generalizability of the study. Despite the loss of some of the practical applications for the Kentwood School District, increasing the sample size would undoubtedly strengthen the generalizability of the findings. Additionally, incorporating other school districts from across the country would help to mitigate highly contextualized factors that may have influenced the study's findings. Through incorporating multiple districts, localized factors that may have influenced the study's findings would be less impactful to the overall results.

Another action that would help increase the generalizability of the study would be to extend the timeframe for the number of cohorts that were analyzed. While this study analyzed four cohorts from 2015-2018, incorporating cohorts from an extended period would help to reduce the impact of a singular event that may have influenced a cohorts' data. The increased timeframe would certainly increase the generalizability.

To account for the students that were excluded from the sample due to incomplete data, a pairwise statistical method could be used to compare the non-missing variables for students without complete data. One drawback of using a pairwise method for missing data is that the assumption that the data is missing completely at random. With student mobility identified as an early warning indicator for potential dropouts (Jimerson et al., 2000; South et al., 2007), the missing data would not be completely random. Although issues may arise, the pairwise method would certainly aid in maximizing all available data.

Another statistical analysis that is suggested for further research is a ROC analysis. ROC analysis would assist in identifying the accuracy and thresholds of each specific independent variable. This information would greatly assist with identifying the thresholds for the study's continuous variable of total number of days absent freshmen year. Number of days were the most impactful for determining potential dropouts.

A final suggestion for further research is to analyze a broader range of early warning indicators with a similar sample to assess their predictive validity of graduation attainment. The EWS field has established a vast array of student variables as potential early warning indicators. With a larger sample size and complete longitudinal data, student variables such as discipline incidents, assessment scores, and elementary literacy abilities could be assessed for their predictive validity. These additional variables may shed more light on predictors of graduation attainment within a rural sample.

Conclusion

For the Kentwood School District 2014-2018 cohorts, socioeconomic status, freshmen absenteeism, and the freshmen on-track indicator all proved to have a statistically significant impact on whether or not a student would be classified as either a 4-year graduate or non-4-year graduate. Students that failed to earn six total credits their freshmen year, were frequently absent, or participated in a free/reduced lunch program were significantly more likely to not graduate within 4 years of beginning high school. These findings were consisted with the broader EWS research field (Allensworth & Easton, 2007; Bowers et al., 2013; Bruce et al., 2011; Gleason & Dynarski, 2002) and will help the Kentwood School District to build a case for improving the levels of support for students who meet these designated criteria in the future.

Through the extensive review of EWS research, data collection, and statistical analysis, one of the most substantial takeaways, personally, was the importance of going beyond simply using early warning indicators to identify potentially at-risk students. While identification of at-risk students is an important first step, to be effective, EWS must incorporate a much broader system of support for students. If an EWS framework is used only to identify at-risk students, and does not match the at-risk student with timely and aligned support, then the identification is essentially worthless. The follow up support for at-risk students once they have been identified is truly the most important and meaningful work of EWS.

Once a student has been identified through early warning indicators, the real work of matching the student to the proper academic, social, emotional, or physical support can take place. Students on the pathway to dropping out desperately need the timely intervention of positive, caring, and knowledge adults. School district that can systematically identify, support, and reengage their at-risk student populations will undoubtedly see an increase in healthy students, schools and communities.

References

2010 Census Urban and Rural Classification and Urban Area Criteria. (2010). Washington D.C. Retrieved from https://www.census.gov/geo/reference/ua/urban-rural-2010.html

Alexander, K. L., Entwisle, D. R., & Horsey, C. S. (1997). From first grade forward: Early foundations of high school dropouts. *American Sociological Association*, *70*(2), 87–107. Retrieved from http://www.jstor.org/stable/2673158

Allensworth, E. (2013). The use of ninth-grade early warning indicators to improve Chicago schools. *Journal of Education for Students Placed at Risk*, *18*(1), 68–83. https://doi.org/10.1080/10824669.2013.745181

Allensworth, E., & Easton, J. (2007). *What matters for staying on-track and graduating in chicago public high schools: A closer look at course grades, failures, and attendance in the freshman year*. *Consortium on Chicago School Research*. Chicago.

Allensworth, E., & Easton, J. (2012). *For ELLS - What matters for staying on-track and graduating in chicago public high schools*. *Consortium on Chicago School Research*. Chicago.

Allensworth, E. M., & Easton, J. Q. (2005). *The on-track indicator as a predictor of high school graduation*. *Consortium on Chicago School Research* (Vol. 49). Chicago. Retrieved from http://www.aaronjmeyer.com/storage/OnTrackIndicator.pdf

Arnold, M. L. (2004). Guiding rural schools and districts: A research agenda. *US Department of Education*, 15. Retrieved from http://eric.ed.gov/ERICWebPortal/recordDetail?accno=ED484397

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing student disengagement and

keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Educational Psychologist*, *42*(4), 223–235. https://doi.org/10.1080/00461520701621079

Balfanz, R., & Legters, N. (2010). Do we have what it takes to put all students on the graduation path? *New Directions for Youth Development*, (127), 11–24. https://doi.org/10.1002/yd

Barfield, K. A., Hartman, J., & Knight, D. (2012). Early warning systems: It's never too early. *Technological Horizons In Education*, *39*(2), 18–20.

Barry, M., & Reschly, A. (2012). Longitudinal predictors of high school completion. *School Psychology Quarterly*, *27*(2), 74–84. https://doi.org/10.1037/a0029189

Bauch, P. (2001). School-Community Partnerships in Rural Schools: Leadership, Renewal, and a Sense of Place. *Peabody Journal of Education*, *76*(2), 75–100. https://doi.org/10.1207/S15327930pje7602

Bowers, A. J. (2010). Grades and graduation: A longitudinal risk perspective to identify student dropouts. *Journal of Educational Research*, *103*(3), 191–207. https://doi.org/10.1080/00220670903382970

Bowers, A. J., Sprott, R., & Taff, S. A. (2013). Do we know who will drop out?: A review of the predictors of dropping out of high school: Precision, sensitivity, and specificity. *The High School Journal*, *96*(2), 77–100. https://doi.org/10.1353/hsj.2013.0000

Boylan, R. L., & Renzulli, L. (2017). Routes and reasons out, Paths back. *Youth & Society*, *49*(1), 46–71. https://doi.org/10.1177/0044118X14522078

Brophy, J. (1982). *Research on the Self-Fulfilling Prophecy and Teacher Expectations*. Washington D.C. Retrieved from https://files.eric.ed.gov/fulltext/ED221530.pdf

Bruce, M., Bridgeland, J., Balfanz, R., & Horning Fox, J. (2011). *On track for success: The use*

of early warning indicator and intervention systems to build a grad dation. Civic Enterprises. Retrieved from http://new.every1graduates.org/wp-content/uploads/2012/03/on_track_for_success.pdf

Budget, O. of M. and. (2010). 2010 Standards for delineating metropolitan and micropolitan statistical areas. *Federal Register*, *75*(123), 1–9.

Burke, A. (2015). *Early identification of high school graduation outcomes in oregon leadership network schools*. *Regional Educational Laboratory Northwest*. Washington D.C.

Byun, S. Y., Meece, J. L., Irvin, M. J., & Hutchins, B. C. (2012). The role of social capital in educational aspirations of rural youth. *Rural Sociology*, *77*(3), 355–379. https://doi.org/10.1111/j.1549-0831.2012.00086.x

Carlsen, W. S., & Monk, D. H. (1992). Differences between rural and nonrural secondary science teachers: Evidence from the Longitudinal Study of American Youth. *Journal of Research in Rural Education*, *8*(2), 1–10. Retrieved from http://php.scripts.psu.edu/dept/jrre/articles/v8,n2,p1-10,Carlsen.pdf

Christenson, S. L., & Thurlow, M. L. (2004). School dropouts: Prevention considerations, interventions, and challenges. *Current Directions in Psychological Science*, *13*(1), 36–39. https://doi.org/10.1111/j.0963-7214.2004.01301010.x

Coladarci, T. (2007). Improving the yield of rural education research: An editor’s swan song. *Journal of Research in Rural Education*, *22*(3), 22–3. Retrieved from http://www.jrre.psu.edu/articles/22-3.htm

Coleman, J. (1988). Social capital in the creation of human capital. *The American Journal of Sociology*, *94*.

Dalton, B., Glennie, E., & Ingels, S. (2009). *Late high school dropouts: Characteristics,*

experiences, and changes across cohorts. *National Center for Education Statistics*. Retrieved from http://www.eric.ed.gov/ERICWebPortal/recordDetail?accno=ED505580%5Cnhttp://nces.ed.gov/pubs2009/2009307.pdf

Darling-Hammond, L. (2000). Teacher quality and student achievement : A review of state policy evidence previous research. *Education Policy Analysis Archives*, *8*(1), 1–44. https://doi.org/10.1038/sj.clp

Davis, M., Herzog, L., & Legters, N. (2013). Organizing schools to address early warning indicators (EWIs): Common practices and challenges. *Journal of Education for Students Placed at Risk*, *18*(1), 84–100. https://doi.org/10.1080/10824669.2013.745210

Debaun, B., & Roc, M. (2013). *Saving futures , saving dollars: The impact of education on crime reduction and earnings*. *Alliance for Excellent Education*.

Dorn, S. (2003). High-stakes testing and the history of graduation. *Education Policy Analysis Archives*, *11*(1), 1–29. Retrieved from http://epaa.asu.edu/epaa/v11n1/

Eckstein, Z., & Wolpin, K. (1999). Why youths drop out of high school: The impact of preference, opportunities, and abilities. *Econometrica*, *67*(6), 1295–1339.

Education, I. D. of. (2017). Freshmen On Track. Retrieved from https://www.illinoisreportcard.com/state.aspx?source=trends&source2=freshmenontrack&Stateid=IL

Education, U. D. of. (2008). *A nation accountable: Twenty-five years after a nation at risk*. Retrieved from http://www.ed.gov/rschstat/research/pubs/accountable/%0AOn

Ensminger, M., & Slusarcick, A. (1992a). Paths to high school graduation or dropout: A longitudinal study of a first-grade cohort. *Sociology The Journal Of The British*

Sociological Association, *65*(2), 95–113. Retrieved from http://www.jstor.org/stable/2112677

Ensminger, M., & Slusarcick, A. (1992b). Paths to high school graduation or dropout: A longitudinal study of a first grade cohort. *Sociology of Education*, *65*(2), 95–113. https://doi.org/10.2307/2112677

Finn, J. (1993). *School engagement and students at risk*. Washington D.C.

Franklin, B. J., & Trouard, S. B. (2016). Comparing dropout predictors for two state-level panels using grade 6 and grade 8 data. *Journal of Educational Research*, *109*(6), 631–639. https://doi.org/10.1080/00220671.2015.1016601

Frazelle, S., & Barton, R. (2013). Implementing early warning systems. *Principal's Research Review*, *8*(4), 1–7.

Frazelle, S., & Nagel, A. (2015). *A practitioner's guide to implementing early warning systems*. Washington D.C. Retrieved from http://ies.ed.gov/ ncee/edlabs.

Gandara, P., Gutiaez, D., & O'Hara, S. (2001). Latino immigrant parents and children learning and publishing together in an after-school setting. *Journal of Education for Students Placed at Risk*, *6*(1–2), 95–113. https://doi.org/10.1207/s15327671espr0601-2

Gibbs, R. (2000). The Challenge Ahead for Rural Schools. *Forum for Applied Research and Public Policy*, *15*(1), 82–91. Retrieved from papers3://publication/uuid/9FE55DED-6AAE-446D-8921-315EAA63900A

Gibbs, R. (2002). Rural labor markets in an era of welfare reform. In B. Weber, G. Duncan, & L. Whitener (Eds.), *Rural Dimensions of Welfare Reform* (pp. 51–76). Kalamazoo.

Gleason, P., & Dynarski, M. (1998). *Do we know whom to serve? Issues in using risk factors to indentify dropouts. School Dropout Demonstration Assistance Program*.

Gleason, P., & Dynarski, M. (2002). Do we know whom to serve? Issues in using risk factors to identify dropouts. *Journal of Education for Students Placed at Risk (JESPAR)*, *7*(1), 25–41. https://doi.org/10.1207/S15327671ESPR0701

Greenberg, E., & Teixeira, A. (1998). Educational achievement in rural schools. In R. Gibbs, P. L. Swaim, & R. Teixeira (Eds.), *Rural Education and Training in the New Economy: The Myth of the Rural Skills Gap* (pp. 33–39). Ames: Iowa State University Press.

Greenberg, M., Weissberg, R., O'Brien, M., Zins, J., Fredericks, L., Resnik, H., & Elias, M. (2003). Enhancing school-based prevention and youth development trough coordinated social, emotional, and academic learning. *American Psychologist*, *58*(6–7), 466–474. https://doi.org/10.1037/0003-066X.58.6-7.466

Haller, E., & Virkler, S. (1993). Another look at rural-nonrural differences in students' educational aspirations. *Journal of Research in Rural Education*, *9*(3), 170–178. Retrieved from http://agris.fao.org/agris-search/search/display.do?f=1995/US/US95198.xml;US9450900

Hammond, C. (2007). *Dropout risk factors and exemplary programs: A technical report*. Clemson.

Hardré, P. L., Crowson, H. M., Debacker, T. K., & White, D. (2007). Predicting the academic motivation of rural high school students. *Journal of Experimental Education*, *75*(4), 247–269. https://doi.org/10.3200/JEXE.75.4.247-269

Hardre, P. L., & Reeve, J. (2003). A motivational model of rural students' intentions to persist in, versus drop out of, high school. *Journal of Educational Psychology*, *95*(2), 347–356. https://doi.org/10.1037/0022-0663.95.2.347

Harlow, C. (2003). *Education and correctional populations*. *Bureau of Justice Statistics Special*

Report. https://doi.org/NCJ 195670

Hektner, J. (1995). When moving up implies moving out: Rural adolescent conflint in transition to adulthood. *Journal of Research in Rural Education*, *11*(1), 3–14.

Helge, D. (1991). *Rural Exceptional At Risk*. Reston: The Council tor Exceptional Children,.

Henry, K. L., Knight, K. E., & Thornberry, T. P. (2012). School disengagement as a predictor of dropout, delinquency, and problem substance use during adolescence and early adulthood. *Journal of Youth and Adolescence*, *41*(2), 156–166. https://doi.org/10.1007/s10964-011-9665-3

Heppen, J. B., & Therriault, S. B. (2008). *Developing early warning systems to identify potential high school dropouts*. *National High School Center*.

Herlihy, C. (2007). State and district-level support for successful transitions into high school. Policy Brief. Retrieved from http://eric.ed.gov/?id=ED501074%5Cnhttp://files.eric.ed.gov/fulltext/ED501074.pdf

Hernandez, D. J. (2011). *Double jeopardy: How third grade reading skills and poverty influence high school graduation*. *Annie E. Casey Foundation*. https://doi.org/10.1080/02568543.2012.711801

Hess, G., Alfred, J., & Lauber, D. (1985). *Dropouts from the chicago public schools: An analysis of the classes of 1982, 1983, 1984*. Chicago.

Hjorth, C. F., Bilgrav, L., Frandsen, L. S., Overgaard, C., Torp-Pedersen, C., Nielsen, B., & Bøggild, H. (2016). Mental health and school dropout across educational levels and genders: A 4.8-year follow-up study. *BMC Public Health*, *16*(1), 1–12. https://doi.org/10.1186/s12889-016-3622-8

Howley, C. W. (2006). Remote possibilities: Rural children's educational aspirations. *Peabody*

Journal of Education, *81*(2), 62–80. https://doi.org/10.1207/S15327930pje8102

Hu, S. (2003). Educational aspirations and postsecondary access and choice: Students in urban, suburban, and rural schools compared. *Education Policy Analysis Archives*, *11*(14), 1–13.

Hummer, R., & Hernandez, E. (2017). *High school and beyond (HS&B) longitudinal study*. Retrieved from https://nces.ed.gov/statprog/handbook/pdf/hsb.pdf

Irving, S. K., & Loveless, T. A. (2015). *Dynamics of economic well-being: Participation in government programs 2009-2012: Who gets assistance? U.S. Census Bureau; Department of Commerce: Economics and Statistics Administration*. Retrieved from http://search.proquest.com/docview/58738487?accountid=13042%5Cnhttp://oxfordsfx.hosted.exlibrisgroup.com/oxford?url_ver=Z39.88-2004&rft_val_fmt=info:ofi/fmt:kev:mtx:book&genre=document&sid=ProQ:PAIS+International&atitle=&title=Dynamics+of+Economic+Well-Be

James, C. (2002). *The 1923 Tokyo Earthquake and Fire*. Berkely.

Jerald, C. D. (2006). *Identifying potential dropouts: Key lessons for building an early warning data system*. *Achieve, Inc.* New York. Retrieved from http://www.achieve.org/files/IdentifyingPotentialDropouts.pdf

Jimerson, S., Egeland, B., Sroufe, A., & Carlson, B. (2000). A prospective longitudinal study of high school dropouts examining multiple predictors across development. *Journal of School Psychology*, *38*(6), 525–549. https://doi.org/10.1016/S0022-4405(00)00051-0

Johnson, E., & Semmelroth, C. (2010). The predictive validity of the early warning system tool. *NASSP Bulletin*, *94*(2), 120–134. https://doi.org/10.1177/0192636510380789

Johnson, J. (2005). Why Rural Matters 2005. *A Report of the Rural School and Community Trust Policy Program*, (May), 1–114. Retrieved from papers3://publication/uuid/09AAD76E-

3909-491E-B3B9-5EEEED8A0014

Johnson, J., & Madden, K. (2010). The rural dropout problem : An invisible achievement gap.

Jordan, J., Genti, K., & Mykerezi, E. (2012). Rural and urban high school dropout rates: Are they different? *Journal of Research in Rural Education*, *27*(12), 1–21. Retrieved from http://jrre.psu.edu/articles/27-12.pdf%0AThis

Jussim, L., & Harber, K. D. (2005). Teacher expectations and self-fulfilling prophecies: Knowns and unknowns, Resolved and unresolved controversies. *Personality and Social Psychology Review*, *9*(2), 121–155. https://doi.org/10.1207/s15327957pspr0902

Kennelly, L., & Monrad, M. (2007). *Approaches to dropout prevention: Heeding early warning signs with appropriate interventions*. *National High School Center*. https://doi.org/10.1037/e538292012-001

Kim, K. N. (2013). Career trajectory in high school dropouts. *The Social Science Journal*, *50*(3), 306–312. https://doi.org/10.1016/j.soscij.2013.03.005

Knoblauch, D., & Chase, M. A. (2015). Rural, suburban, and urban schools: The impact of school setting onthe efficacy beliefs and attributions of student teachers. *Teaching and Teacher Education*, *45*, 104e114-114. https://doi.org/10.1016/j.tate.2014.10.001

Knowles, J. (2016). Of needles and haystacks: Building an accurate statewide dropout early warning system in wisconsin. *Journal of Educational Data Mining*, *7*(3), 18–67. https://doi.org/doi:10.6084/m9.figshare.1142580

Koon, S., & Petscher, Y. (2015). *Comparing methodologies for developing an early warning system: Classification and regression tree model versus logistic regression*. *U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Southeast*.

Washington D.C. Retrieved from http://ies.ed.gov/ncee/edlabs.

Kupersmidt, J. B., & Coie, J. D. (1990). Preadolescent peer status, aggression, and school adjustment as predictors of externalizing problems in adolescence. *Child Development*, *61*(5), 1350–1362. Retrieved from http://www.jstor.org/stable/1130747

Levin, H. M., Belfield, C. R., & Rouse, C. (2007). *The costs and benefits of an excellent education for all of america's children*. New York.

Lichter, D., & Egeebeen, D. (1992). Child poverty and the changing rural family. *Rural Sociology*, *57*(2), 151.

Lloyd, D. N. (1978). Prediction of school failure from third-grade data. *Educational and Psychological Measurement*, *38*, 1193–1200.

Lowe, J. M. (Idaho S. U. (2006). Rural education: Attracting and retaining teachers in small schools. *The Rural Educator*, *Winter*(2), 28–32. Retrieved from http://www.ruraleducator.net/archive/27-2/27-2_Lowe.pdf

Mac Iver, M. A. (2013). Early warning indicators of high school outcomes. *Journal of Education for Students Placed at Risk (JESPAR)*, *18*(1), 1–6. https://doi.org/10.1080/10824669.2013.745375

Mac Iver, M. A., & Messel, M. (2013). The ABCs of keeping on track to graduation: Research findings from baltimore. *Journal of Education for Students Placed at Risk (JESPAR)*, *18*(1), 50–67. https://doi.org/10.1080/10824669.2013.745207

Mac Iver, M., & Mac Iver, D. (2010). How do we ensure that everyone graduates? An integrated prevention and tiered intervention model for schools and districts. *New Directions for Youth Development*, (127), 25–35. https://doi.org/10.1002/yd

Malhoit, G. C. (2005). Providing rural students with a high quality education: The rural

perspective on the concept of educational adequacy. *Rural School and Community Trust*, (July).

Marsh, H. W., & Martin, A. J. (2011). Academic self-concept and academic achievement: Relations and causal ordering. *British Journal of Educational Psychology*, *81*(1), 59–77. https://doi.org/10.1348/000709910X503501

McFarland, J., Cui, J., & Stark, P. (2018). Trends in high school dropout and completion rates in the United States: 2014, 75. Retrieved from https://nces.ed.gov/pubs2018/2018117.pdf

Mcfarland, J., Hussar, B., Brey, C., Snyder, T., Wang, X., Wikinson-Flicker, S., … Ossolinski, M. (2017). *The condition of education 2017*. Washington D.C. Retrieved from https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2017144

Mensch, B., & Kandel, D. (2018). Dropping out of high school and drug involvement. *Sociology of Education*, *61*(2), 95–113.

Monk, D. H. (2007). Recruiting and retaining high-quality teachers in rural areas recruiting and retaining high-quality teachers in rural areas, *17*(1), 155–174. https://doi.org/10.1353/foc.2007.0009

Montecel, M. R., Cortez, J. D., & Cortez, A. (2004). Dropout-prevention programs: Right intent, wrong focus, and some suggestions on where to go from here. *Education and Urban Society*, *36*(2), 169–188. https://doi.org/10.1177/0013124503261327

Muller, A. (2002). Education, income inequality, and mortality: A multiple regression analysis. *The British Medical Journal*, (324), 23–25. https://doi.org/10.1007/SpringerReference_6072

Nadel, W., & Sagaway, S. (2002). *America's Forgotten Children: Child Poverty in Rural America.*

National Center for Education Statistics. (2013). The status of rural education, *11*(Ccd), 1–7.

Retrieved from http://nces.ed.gov/programs/coe/indicator_tla.asp

National Commission on Excellence in Education. (1983). *A nation at risk: The imperative for educational reform*. Washington D.C. https://doi.org/10.2307/3323945

National Police Agency of Japan. (2018). *Police Countermeasures and Damage Situation associated with 2011Tohoku district - off the Pacific Ocean Earthquake*. Retrieved from http://www.npa.go.jp/archive/keibi/biki/higaijokyo_e.pdf

Neild, R. C., & Balfanz, R. (2006). *Unfulfilled promise: The dimensions and characteristics of philadelphia's dropout crisis, 2000-2005*. Philadelphia.

Neild, R. C., Balfanz, R., & Herzog, L. (2007). An early warning system. *Educational Leadership*, *65*(2), 28–33.

Office of Accountability, Research, & I. S. (2017). *Freshman on-track as a predictor of junior year achievement and outcomes*. *Data Brief*.

Oregon Department of Education. (2015). *Cohort Graduation Rate Policy and Technical Manual*.

Oregon Department of Education. (2018). *Dropout Rate and Exit Adjustment Policy and Technical Manual*. Salem. Retrieved from https://www.oregon.gov/ode/reports-and-data/students/Documents/dropout_exitadj_manual_201718.pdf

Paasch, K. M., & Swaim, P. L. (1993). More rural students are graduating from high school, but a serious dropout problem remains. *Rural Development Perspectives*, *10*(3), 24–34.

Pierret, C. (2005). *The national longitudinal survey of youth: 1979 cohort at 25*. *Monthly Labor Review*. Washington D.C.

Pinkus, L. (2008). *Using early-warning data to improve graduation rates: Closing cracks in the education system*. Washington D.C. Retrieved from

http://beta.fresnounified.org/gradtf/Shared Documents/Using Early Warning Data to Improve Graduation Rates, Closing Cracks in the Education System.pdf

Ratcliffe, M., Burd, C., Holder, K., & Fields, A. (2016). Defining Rural at the U.S. Census Bureau. *US Census*, (December), 1–8. https://doi.org/10.13140/RG.2.2.16410.64969

Reid, J. (1989). The Rural Economy and Rural Youth: Challenges for the Future. *Research in Rural Education*, *6*(2), 17–23. Retrieved from http://www.eric.ed.gov/ERICWebPortal/recordDetail?accno=EJ407456

Roderick, M. (1993). *The path to dropping out*. Westport: Auburn House.

Ronfeldt, M., Loeb, S., & Wyckoff, J. (2013). How teacher turnover harms student achievement. *American Educational Research Journal*, *50*(1), 4–36. https://doi.org/10.3102/0002831212463813

Roscigno, V. J., & Crowley, M. L. (2001). Rurality, institutional disadvantage, and achievement attainment. *Rural Sociology*, *66*(2), 268–292. https://doi.org/10.1111/j.1549-0831.2001.tb00067.x

Roscigno, V., Tomaskovic-Devey, D., & Crowley, M. (2006). Education and the inequalities of place. *Social Forces*, *84*(4), 2121–2145. https://doi.org/10.1353/sof.2006.0108

Rosenthal, B. S. (1998). Non-school correlates of dropout: An integrative review of the literature. *Children and Youth Services Review*, *20*(5), 413–433. https://doi.org/10.1016/S0190-7409(98)00015-2

Rumberger, R. (2011). *Dropping out* (1st ed.). Cambridge: Harvard University Press. https://doi.org/10.1016/0047-2352(73)90016-0

Rumberger, R. W. (1987). High school dropouts: A review of issues and evidence. *Review of Educational Research*, *57*(2), 101–121. https://doi.org/10.3102/00346543057002101

Rumberger, R. W. (1995). Dropping out of Middle School: A Multilevel Analysis of Students and Schools. *American Educational Research Journal*, *32*(3), 583. https://doi.org/10.2307/1163325

Rumberger, R. W., & Lim, S. A. (2008). *Why students drop out of school: A review of 25 years of research*. Santa Barbara. Retrieved from http://www.cdrp.ucsb.edu/pubs_reports.htm

Rumberger, R. W., & Palardy, G. J. (2005). Test scores, dropout rates, and transfer rates as alternative indicators of high school performance. *American Educational Research Journal*, *42*(1), 3–42. https://doi.org/10.3102/00028312042001003

Saunders, M., Silver, D., & Zarate, E. (2008). *The impact of high schools on student achievement within the los angeles unified school district: A value-added approach*. Los Angeles.

Schafft, K. (2006). Poverty, residential mobility, and student transiency within a tural New York School district. *Rural Sociology*, *71*(2), 212–231.

Schoeneberger, J. (2012). Longitudinal attendance patterns: Developing high school dropouts. *The Clearing House: A Journal of Educational …*, *85*(1), 7–14. https://doi.org/10.1080/00098655.2011.603766

Soland, J. (2013). Predicting high school graduation and college enrollment: Comparing early warning indicator data and teacher intuition. *Journal of Education for Students Placed at Risk*, *18*(3), 233–262. https://doi.org/10.1080/10824669.2013.833047

South, S. J., Haynie, D. L., & Bose, S. (2007). Student mobility and school dropout. *Social Science Research*, *36*(1), 68–94. https://doi.org/10.1016/j.ssresearch.2005.10.001

Statistics, L. (2015). Binomial logistic regression using SPSS statistics. Retrieved from https://statistics.laerd.com

Stearns, E., & Glennie, E. J. (2006). When and why dropouts leave high school. *Youth and*

Society, *38*(1), 29–57. https://doi.org/10.1177/0044118X05282764

Strange, M. (2011). Finding fairness for rural students. *Phi Delta Kappan*, *92*(6), 8–15. https://doi.org/10.1177/003172171109200603

Stuit, D., Norbury, H., O'Cummings, M., Heppen, J., Dhillon, S., Lindsay, J., & Zhu, B. (2016). *Identifying early warning indicators in three ohio school districts*. Washington D.C. Retrieved from http://ies.ed.gov/ncee/edlabs

Suh, S., Suh, J., & Houston, I. (2007). Predictors of categorical at-risk high school dropouts. *Journal of Counseling and Development*, *85*(2), 196–203. https://doi.org/10.1002/j.1556-6678.2007.tb00463.x

Swanson, C. B., & Chaplin, D. (2003). *Counting high school graduates when graduates count; Measuring graduation rates under the high stakes of NCLB*. Washington D.C.

Talbot, D. (2011). 80 Seconds of Warning for Tokyo. *MIT Technology Review*. Retrieved from https://www.technologyreview.com/s/423274/80-seconds-of-warning-for-tokyo/

Toby, J., Armor, D. J., & Jim, O. (1992). Carrots or sticks for high school dropouts? *Public Interest*, (106), 76–90.

Tompkins, R., & Deloney, P. (1994). *Rural students at risk in Arkansas, Louisiana, New Mexico, Oklahoma, and Texas*. Austin. Retrieved from http://files.eric.ed.gov/fulltext/ED388477.pdf

U.S. Bureau of Labor and Statistics. (2014). *More education, less unemployment*. *Occupational Outlook Quarterly*. Washington D.C.

U.S. Bureau of Labor Statistics. (2016). *Usual Weekly Earnings of Wage and Salary Workers: Third Quarter 2016*. *News Release*. Retrieved from https://www.bls.gov/news.release/wkyeng.toc.htm

U.S. Department of Education. (2001). Twenty-third Annual Report to Congress on the

Implementation of the Individuals with Disabilities Education Act. Retrieved from https://www2.ed.gov/about/reports/annual/osep/2001/toc-execsum.pdf

Uekawa, K., Merola, S., Fernandez, F., & Porowski, A. (2010). *Creating an early warning system: Predictors of dropout in delaware*.

Valentine, J., DuBois, D., & Cooper, H. (2004). The Relation Between Self-Belifs and Academic Achievement: A Meta-Analytic Review. *Educational Psychologist*, *39*(2), 111–133. https://doi.org/10.1207/s15326985ep3902_3

Uekawa, K., Merola, S., Fernandez, F., & Porowski, A. (2010). Creating an early warning system: Predictors of dropout in Delaware. *Mid-Atlantic Regional Education Laboratory*. Retrieved from https://files.eric.ed.gov/fulltext/ED565682.pdf

Appendix A: IRB Request Form

IRB Request Form

Project Information	
Project Title: The Impact of Freshmen On-Track Status, Absenteeism, and Associated Demographic Variables on Four-Year Graduation Attainment within a Rural Community: A Predictive Validity Study	Project Number:
Site IRB Number:	Sponsor:
Principal Investigator: Joel Hoff	Organization: Kentwood SD
Location: Kentwood School District	Phone: 541-416-6900 ext. 3105
Other Investigators: Dr. Dane Joseph	Organization: George Fox University
Location: GFU-Newberg Campus	Phone: 503-554-2855

1. *PURPOSE OF THIS RESEARCH STUDY*
    - This study will analyze whether a student's freshmen year attendance rate and credit accumulation have a relationship with whether or not the student graduates high school within 4 years.
2. *PROCEDURES*
    - This quantitative secondary data correlational study will use multiple logistic regression to determine the predictive ability of chronic absenteeism and freshmen year credit accumulation for 4-year graduation attainment. The student data will be retrieved from the Oregon Department of Education Achievement Data Insight and analyzed using SPSS.
3. *POSSIBLE RISKS OR DISCOMFORT*
    - As this study will be a secondary dataset analysis, there is very low risk for the students whose data will be analyzed.
4. *OWNERSHIP AND DOCUMENTATION OF SPECIMENS*
    - Student data will be downloaded from the ODE Achievement Data Insight and saved as a password protected file on the researcher's password protected computer.
5. *POSSIBLE BENEFITS*
    - The study will benefit the educational field by providing additional insight regarding the relationship between the freshmen on-track indicator and chronic

absenteeism with 4-year graduation attainment within a semi-rural public school setting.

6. *FINANCIAL CONSIDERATIONS*
    - There are no financial benefits or considerations regarding the participants of this study.
7. *AVAILABLE TREATMENT ALTERNATIVES*
    - Not Applicable
8. *AVAILABLE MEDICAL TREATMENT FOR ADVERSE EXPERIENCES*
    - Not Applicable
9. *CONFIDENTIALITY*
    - This study will not use any specific individual student identifiers. The data will be downloaded and saved as a password protected file on the researcher's password protected laptop.
10. *TERMINATION OF RESEARCH STUDY*

    A missing value analysis will be used once the student data set is received. Only students with a complete data set will be analyzed. The student data will be downloaded after completion of the IRB process and will be destroyed per the ODE guidelines once the dissertation process is complete.

11. *AVAILABLE SOURCES OF INFORMATION*
    - Any further questions you have about this study will be answered by the Principal Investigator:

      Name: Joel Hoff
      Phone Number: 541-954-0643

    - Any questions you may have about your rights as a research subject will be answered by:

      Name: Dr. Dane Joseph
      Phone Number: 503-554-2855

    - In case of a research-related emergency, call: Joel Hoff

      Day Emergency Number: 541-954-0643
      Night Emergency Number: 541-954-0643

12. *AUTHORIZATION*

    I have read and understand this consent form, and grant permission for Crook County School District student data for the classes of 2014 - 2018 freshmen on-track, absenteeism, and demographic data to be used in this research study. I understand that I will receive a copy of this form. I voluntarily choose to participate, but I understand that my consent does not take away any legal rights in the case of negligence or other legal

fault of anyone who is involved in this study. I further understand that nothing in this consent form is intended to replace any applicable Federal, state, or local laws.

Participant Name (Printed or Typed):

Date:

Participant Signature:
Date:

Principal Investigator Signature:
Date:

Signature of Person Obtaining Consent:
Date: