EVALUATING THE EFFICACY OF AN EARLY WARNING SYSTEM IN PREDICTING POSTSECONDARY OUTCOMES: A PATH ANALYSIS

By

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Abstract

An extensive body of research has shown that data-driven Early Warning Systems (EWS) are an effective tool for reducing school dropout. EWS designed to prevent dropout flags at-risk students based on a core set of indicators, including attendance, behavior, and course failures. While preventing high school dropout is a critical step to ensuring student success, in today's 21st century workforce, a high school diploma is not enough. To strategically align interventions and strategies designed to promote college readiness, school districts must be aware of the variables that predict postsecondary success. Unfortunately, there is a dearth of succinct college readiness tools that capture multiple longitudinal indictors that can be used to identify and flag students who are not ready to meet the rigorous demands of postsecondary education. To fill this gap, the present study evaluated the utility of the core EWS dropout indicators in predicting postsecondary success. This study examined longitudinal data from 7th through 12th grade to predict postsecondary outcomes from one moderately sized Midwestern school district. A series of path analyses was used to analyze retrospective data from approximately 3,080 public school students who entered 7th grade in the 2007-08 school year and had an original on-time graduation year of 2013. Results revealed a statistically significant temporal relationship among each of the key EWS variables (i.e., attendance, behavior, GPA, and state assessment scores) across the target six years. In terms of the predictive validity of the EWS indicators, the study found that 12th grade attendance rate, 12th grade GPA, and 7th grade GPA were statistically significant predictors of postsecondary enrollment. Free and reduced priced lunch status, special education status, and mobility status were also statistically significant predictors of enrollment as well. The study also found that 11th grade GPA and 7th grade GPA were statistically significant predictors of postsecondary persistence. Similarly, the persistence model also indicated that free and reduced priced lunch status, special education status, and mobility status were statistically significant predictors. The study discusses the significance of these findings in light of prior research, the implications for practice, future directions for research, and limitations.

Dedication

For my mom –

You were always my biggest fan and cheerleader. I would not be where I am today without the years of love and support you gave me. I love you and miss you every day!
This dissertation is for you.

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Introduction

In 2009, President Obama sent out a call to action focusing on increasing college and career readiness (Address to Joint Session of Congress, 2009). In order to meet the President's vision, school districts are being called upon to increase graduation rates as a means for preparing students to be college and career ready. To accomplish this goal, districts and policymakers alike espoused innovative methods to identify and serve at-risk students. A paramount result of these efforts has been a ubiquitous adoption of an early warning system (EWS) as a dropout prevention tool (Soland, 2013). An EWS is a data-driven diagnostic system designed to identify at-risk students, based on a set of highly predictive indicator variables (Allensworth & Easton, 2005; Gleason & Dynarsk, 2002).

Research has conclusively found that dropping out of high school is associated with a myriad of negative outcomes that impact individuals, families, and communities (e.g., Levin, Belfield, Muennig, & Rouse, 2006; Mitra, 2014; Muennig, 2007; Rouse, 2007). One major consequence of dropping out of high school is a significant reduction in earning potential. For example, on average, high school dropouts earn approximately $9,000 less per year than high school graduates (Ewert, 2012). To prevent students from encountering these negative impacts, school districts are tasked with providing effective prevention and intervention strategies designed to keep students in school and on-track to graduate. Implementing effective prevention and intervention strategies begins by first identifying at-risk students. Since most schools already track several student-level variables, such as grades, attendance, and disciplinary referrals, implementing and designing an EWS that utilizes these variables was a logical choice to inform dropout programming (Allensworth & Easton, 2007; Curran Neild, 2009; Jerald, 2006a; Pinkus, 2008).

Similar to other educational initiatives, the EWS has undergone several modifications and enhancements. In its inception, the EWS consisted of a dichotomous variable, the on-track indicator, which consisted of aggregated data from student's freshman year of high school used to classify students as either on- or off-track for high school graduation (Allensworth & Easton, 2005). Over time, the EWS became a more robust system that has adopted additional high school indicator variables, including the number of failed courses in all subjects, grade point average (GPA), and attendance rates (Heppen & Therriault, 2008). The key variables used in the EWS are often referred to as the ABCs of dropout – attendance, behavior, and course performance (Balfanz, Herzog, & Mac Iver, 2007). Because dropping out of high school is a gradual process that begins far before students ever step foot on a high school campus (Alexander, Entwisle, & Horsey, 1997; Curran Neild, 2009), the EWS (adhering to its namesake) has extended its scope downward to include pertinent data from middle school (Balfanz et al., 2007).

Prior research can serve as a guide for districts as they design their own EWS. However, the research literature suggests that school districts should use extant, local data to identify the most salient variables related to dropout within the local educational context (Jerald, 2006a; Pinkus, 2008). Because local and state policies influence the climate and culture of school districts, the most pronounced EWS variables may vary from district to district. When school districts are building their EWS, researchers suggest that districts should think about how each selected variable will inform and enhance dropout interventions (Pinkus, 2008). Creating an EWS related to the specific needs of the district's student population will help ensure the successful uptake of the system, which will hopefully increase high school graduation rates within the district.

While preventing high school dropout is a critical step to ensuring student success, in today's 21st century workforce, a high school diploma is not enough. It has been projected that by the year 2020, approximately 63% of jobs nationwide will require postsecondary education for an entry-level position (Georgetown University Center on Education, 2013). The rising demand for postsecondary qualifications in the labor market has a direct impact on secondary education. This is evidenced by the Common Core Standards strong emphasis on preparing students to succeed in credit-bearing college courses (Conley, Drummond, de Gonzalez, Rooseboom, & Stout, 2011). Unfortunately, research has found a large number of students who enter college upon high school graduation are not academically prepared to succeed at these institutions (e.g., ACT, 2015; Greene & Forster, 2003; Royster, Gross, & Hochbein, 2015). To increase the college readiness of high school students, school districts must be aware of the variables that predict eventual postsecondary success. Since many districts have already adopted an EWS to identify students at-risk of dropping out, this system could serve a dual purpose and provide critical information on student's levels of college readiness (Data Quality Campaign, 2013).

A rich body of research has identified variables associated with college readiness (e.g., ACT 2008; 2015, Belfield & Crosta, 2012; Lee, 2012; Zhao & Liu, 2011). The variables identified throughout this body of research significantly overlap with the variables identified within the dropout literature, including high school GPA, performance on college entrance exams, and high school course selection. Given the large amount of overlapping data found within each target area, there appears to be great potential for integrating the college readiness and dropout prevention initiatives into one dynamic EWS.

Currently there is a dearth of research on the efficacy of the EWS on identifying students who are both prepared and underprepared to meet the rigorous demands of postsecondary education (e.g., Becker, Hall, Levinger, Sims, & Whittington, 2014; Soland, 2013). The present study addresses this need by researching the utility of the core EWS dropout indicators (e.g., attendance rates, behavioral incidents, grades, and academic assessment performance) using data from one moderately sized Midwestern school district. This study examines longitudinal data from middle through high school, to predict postsecondary outcomes including initial enrollment and persistence.

One limitation of the past literature involves generalizing findings from large, heavily urbanized districts to smaller districts. The majority of the research on EWS has been conducted in the following major U.S. cities: Chicago, New York, Baltimore, Dallas, and Philadelphia. It is likely that smaller districts do not face the same challenges seen in these larger metropolitan areas. For example, research has found that smaller districts tend to have different spending patterns than larger districts, which may impact the availability of funds to allocate towards dropout initiatives (Boser, 2013). Specifically, research has found that smaller districts often spend more on overhead costs (e.g., administrator salaries, building and maintenance costs) compared to larger districts (Boser, 2013). Further, the demographic composition of smaller less urban districts tend to be less diverse, which may have potential implications on which early warning indicators are the most predictive of both dropout and college readiness. Additional research on EWS should verify that these same early warning indicators are effective for smaller, less urbanized districts.

Of the studies available that have begun to examine the EWS predictive validity on assessing postsecondary outcomes, analyses only include a handful of early warning indicator data obtained from a snapshot in time (e.g., 9th grade end of year GPA). Research indicates that academic decisions, such as dropping out or attending college, are influenced by a multitude of academic experiences that happen over time (e.g., Belfanz, et al., 2007; Christenson & Thurlow, 2004; Curran Neild, 2009). Failing to analyze data through a longitudinal lens may limit the interpretation of the impact of the early warning indicator variables. Further, using data obtained from one time point does not provide information on "sensitive" periods where students may be especially susceptible to falling off track for college readiness. The current study addresses this limitation by evaluating early warning indicators spanning from 7th through 12th grade.

Finally, of the studies that have investigated the predictive validity of early warning indicators on postsecondary outcomes, the majority examined postsecondary success in terms of immediate college enrollment. This study will expand the scope of the predictive validity of the indicator variables by including persistence as an outcome measure of postsecondary success.

The purpose of this study is to investigate the utility of the core indicators of the EWS in predicting postsecondary outcomes, including postsecondary enrollment immediately following high school graduation and postsecondary persistence through six semesters in college. This study analyzes early warning indicator data for the graduating class of 2013 from one moderately sized school district located in the Midwestern United States. This study includes data on attendance rates, behavioral incidents, state assessment scores, and academic performance measured by GPA spanning from 7th to 12th grade. Path analyses utilizing probit regression techniques were used to analyze the data. This approach is a more robust technique than traditional regression techniques because it simultaneously analyzes the impact of multiple paths and can handle predictor variables that are highly correlated which one another (Finkel, 1995; Keith, 2006).

The next chapter provides a brief history of the emergence of the EWS in the American educational system, and then discusses the most prominent early warning indicators used to predict dropout. The chapter continues with a review of key variables used to assess college readiness and predict later college success. Finally, the chapter concludes with an examination of the narrow body of literature focused on the integration of the college readiness framework into the dropout EWS.

Chapter II

Review of the Literature

The chapter begins by chronicling the emergence of the dropout Early Warning System (EWS) used within the American educational system. A substantial portion of this section focuses on the indicators and predictors of dropout used in EWSs. A description of how school districts can build an EWS is provided, followed by an overview of the efficacy of this tool in identifying students who may be at-risk of dropping out of school. The chapter then covers the literature on postsecondary enrollment and success, starting with an exploration of current trends in college-going behavior among high school graduates. The chapter continues with a review of the literature on college readiness and the associated indicator variables. Next, the chapter gives a brief overview of the induction of college readiness into an EWS framework, highlighting the dearth of research in this area. The following section operationalizes college success and accentuates measures commonly used to capture this outcome. The chapter concludes with a summary of the main findings and limitations of the literature and a brief description of the current study, including the research questions and hypotheses.

History of Early Warning Systems

High school graduation rate is a metric often used to gauge the success and performance of the American educational system, as well as a proxy for the general health of American society (Heckman & LaFontaine, 2010). High school graduation rate is a good proxy to measure success, as a large body of research highlights the positive benefits of earning a high school diploma (e.g., Levin et al., 2006; Mitra, 2014; Muennig, 2007). For example, over the course of a lifetime, students who earn a high school diploma are projected to make $630,000 more than a student who dropped out of school prior to earning their diploma (Rouse, 2007). Unfortunately, almost one-third of all public school students leave school prior to graduating each year (Snyder & Dillow, 2010). This high percentage of students leaving school prior to graduation accentuates an area of need within the American educational system.

To combat this issue, educational researchers and school districts have engaged in ongoing efforts to develop and implement effective dropout initiatives (Christenson & Thurlow, 2004; Dynarski, Clarke, Cobb, Finn, Rumberger, & Smink, 2008; Kemple, Herlihy, & Smith, 2005; Mccallumore & Sparapani, 2010; Quint, Miller, Pastor, & Cytron, 1999). To increase the likelihood of success of an initiative of this sort, it is important to first identify the target population, specifically students who are at-risk of dropping out of school prior to graduation. In the past decade, EWSs have become a popular tool educators have embraced to inform dropout initiatives and prevention planning efforts. An EWS is a data-driven, diagnostic system that often includes data on student attendance, behavior, and academic achievement (Allensworth & Easton, 2007; Davis, Herzog, & Legters, 2013; Dynarski, et al., 2008; Frazelle, & Nagel, 2015; Kennelly & Monrad, 2007; Knowles, 2015). The EWS is intended to provide information about both student-level and school-wide factors associated with high school dropout, with an emphasis on malleable variables that can be reasonably altered. This information is intended to help school personnel identify those students who are most at-risk for dropping out with the hope that appropriate intervention can help these students complete school (Curran Neild, Balfanz, & Herzog, 2007; Dynarski et al., 2008; Jerald, 2006b). The following section highlights the advent of the EWS in the American educational system.

High School. In 1999, the Consortium on Chicago School Research (CCSR) introduced the precursor to the EWS, the *on-track indicator*. The CCSR partnered with the Chicago Public School District to implement this tool with the 1999 freshman cohort. The development of the on-track indicator was grounded in previous research that demonstrated that four key variables observed during the freshman year of high school were significantly and uniquely correlated with high school graduation: 1) number of F grades in core courses, 2) number of credits earned during freshman year, 3) attendance rates, and 4) end-of-year grade point averages [GPAs] (e.g., Allensworth & Easton, 2005; Coley, 1995; Finn, 1993; Roderick, 1993, 2006; Roderick & Camburn, 1999). Based on this information, the on-track indicator was created by combining two of the key indicators: 1) credits earned and 2) number of failed core courses (i.e., English, math, science, and social studies). Data from these two variables were aggregated to create a dynamic dichotomous variable, characterizing students as either *on-track* or *off-track*. Allensworth and Easton (2005) indicated that these two variables were selected because each contained important information relevant to Chicago Public School's policy about graduation.

The CCRS defined on-track status as earning the minimum number of credits necessary to be promoted to the next grade level (i.e., five full course credits) and not failing more than one core subject during the first two semesters of high school (Allensworth & Easton, 2005; Allensworth, 2013). Results revealed that the on-track indicator was highly predictive of high school graduation. Among the freshman cohort attending school in Chicago Public Schools in 1999, those who were classified as on-track by the end of their freshman year were more than 3.5 times more likely to graduate than students who were classified as off-track. Allensworth and Easton (2005) found that the on-track indicator was a better predictor of high school graduation than students' background characteristics (e.g., ethnicity, gender, socioeconomic status) and middle school academic performance. For example, after controlling for 8th grade achievement test scores, 81% of on-track students graduated within four years, whereas only 22% of off-track students graduated in four years (Allensworth & Easton, 2005). This provided an initial foundation for the use of these indicators to help predict high school graduation.

Similar results were found in other studies that used the on-track indicator classification system during 9^{th} grade to predict high school graduation (Cohen & Smerdon, 2009, Curran Neild, 2009; Kemple, Segeritz, & Stephenson, 2013; Montgomery, Roderrick, & Bolz, 2009; Parthenon Group, 2005, 2008). For example, researchers from the Value-Added Research Center (VARC) partnered with the Milwaukee Public School District to examine the utility of the on-track indicator. Drawing on the work conducted by the CCRS, the EWS used by Milwaukee Public Schools included the on-track indicator as a flag for dropout. Researchers found that this indicator was highly predictive of student graduation, just as it had been in Chicago: 93% of first-time 9^{th} grade students who were on-track graduated high school on time, compared to only 50% of students who were off-track (Carl, Richardson, Cheng, Kim, & Meyer, 2013). These promising results helped show that graduation could be predicted early on in a student's high school career, and paved the way for the development of a more comprehensive EWS.

Unfortunately, relying on one measure, the on-track indicator, to predict dropout behavior was hindered by several issues. For example, using a singular binary on-track measure does not provide information on how far on- or off-track students are with respect to on-time high school graduation (Carl et al., 2013). There may be substantial differences in the levels of support needed by students who are categorized as off-track, but the on-track indicator did not capture this detail. By reducing quantitative information that may be continuous or interval-level data (e.g., academic and behavioral indicators) into a simple binary (i.e., yes/no) variable, the specific level of risk is lost. Additionally, the on-track indicator was designed as a measure of *adequate*

9th grade performance, which provides little to no information on whether students are acquiring the necessary skills to do well in advanced classes or postsecondary work (Allensworth & Easton, 2005). Researchers agreed that additional indicators would be needed to assess higher levels of performance and more fully evaluate student's performance and eventual success (Allensworth & Easton, 2005; Carl et al., 2013; Parthenon Group, 2005).

In 2008, the National High School Center (NHSC) created a free Microsoft Excel® (National High School Center, 2011) template to flag 9th grade students who were off-track for on-time graduation[1]. To address concerns with reliance on a single predictor, the NHSC extended the work conducted by the CCRS by including three additional indicators in their system: 1) the number of failed courses in all subjects, 2) GPA, and 3) attendance rates (Heppen & Therriault, 2008). The NHSC encourages school districts to adopt this free tool and align their data collection system by either incorporating data from the school's main data system or integrating the functions of the tool into their own system (Heppen & Therriault, 2008). The Excel workbook contains several worksheets for analyzing student data, which include built-in flags to indicate whether or not the student is at-risk for dropout with regard to each specific variable.

Previous research provided guidance on how to operationalize the additional indicators used in the NHSC program, as well as set benchmarks for flagging students at-risk. For example, the NHSC threshold for identifying a student as at-risk for GPA is defined as a cumulative GPA less than 2.00. This threshold was set based on findings from Allensworth and Easton's (2007) work which found that 72% of students with a 2.00 GPA at the end of freshman

[1] On-time graduation in this paper refers to the completion of a regular high school diploma within 4 years of entering high school. A regular high school diploma means the standard high school diploma awarded to students in a state that is fully aligned with the state's academic content standards and does not include a high school equivalency credential, certificate of attendance, or any alternative award (Stetser & Stillwell, 2014).

year graduated on-time, while only 53% of students with a 1.50 GPA graduated high school in four years. Allensworth and Easton's (2007) study also influenced the operational definitions of the other additional indictors. The threshold for attendance was designated as missing 10% or more of instructional time. Students who missed 5-9 days per semester had an on-time graduation rate of 63%, students who missed 10-14 days had an on-time graduation rate of 41%, and students who missed 15-19 days per semester had an on-time graduation rate of only 21% (Allensworth & Easton, 2007). Failing two or more courses in any subject was set as the flag for course failures. Allensworth and Easton (2007) found that students who failed just one course had an on-time graduation rate of 70%; however, when students failed two or more courses the graduation rate declined to 55% and the rate continued to decline with each subsequent failure.

To further enhance the predictors used in the EWS, Carl and colleagues (2013) developed the Total Quality Credit (TQC) indicator. The intended purpose of this indicator was to capture both academic quantity (i.e., credits earned) and academic quality (i.e., grades earned). The TQC is a linear combination of credit attainment and final cumulative grade point average in the four core courses, including mathematics English, science, and social studies (Carl et al., 2013). Specifically, the TQC is equal to the number of credits earned multiplied by the numerical equivalent of the cumulative grade earned in the core courses (i.e., A = 4; B = 3, C = 2, D = 1, and F = 0). For example, if a student took four core courses for both semesters and earned a cumulative GPA in the core courses of a 4.00, their TQC would equal 16 (i.e., 4 credits x 4.00 GPA). Carl and colleagues found that the TQC correctly predicted on-time graduation for approximately 85% of students. The TQC provides a more robust representation of the student's academic history, which may be more useful in predicting outcomes beyond high school graduation, such as college enrollment (Carl et al., 2013), persistence and success in college.

Unfortunately, there is no grade level at which high school students are immune to dropping out (Bowers, 2010; Curran Neild & Balfanz, 2006). To accommodate this concern, the EWS expanded its scope from only including data from the freshman year of high school to capture relevant data across grades 10-12. While including relevant data from upper-grade levels in an EWS provides a more comprehensive student profile, it is important to note that predicting dropout among upper-grade levels is more difficult than earlier years of high school because fewer students decide to drop out in the later grades (Curran Neild & Balfanz, 2006).

Middle School. As EWSs garnered attention and research substantiated the efficacy of this tool for flagging students in high school as being at-risk of dropping out (e.g., Allensworth & Easton, 2007; Carl et al., 2013; Curran Neild, 2009; Jerald, 2006a, 2006b; Heppen & Therriault, 2008; Pinkus, 2008), researchers were compelled to modify the tool to encompass performance in middle school. The research literature indicates that the decision to drop out of high school is a gradual process that begins long before students ever step foot on a high school campus (Belfanz et al., 2007; Balfanz, 2009; Carl et al. 2013; Christenson & Thurlow, 2004; Curran Neild, 2009; Curran Neild et al., 2007). Therefore, it was pertinent that the EWS adhere to its namesake and extend downward into middle school.

To support this downward extension, researchers from the Center for the Social Organization of Schools at Johns Hopkins University in conjunction with Philadelphia Public Schools found that the "ABC" indicators (i.e., attendance, behavior, and course completion) utilized by most EWS were valid predictors of high school graduation using both middle and high school student-level data (Balfanz et al., 2007; Curran Neild & Balfanz, 2006). Balfanz and colleagues (2007) used longitudinal analyses to investigate and identify indicators in 6th grade that predicted future dropout. Consistent with findings from other studies (e.g., Allensworth &

Easton, 2007), Balfanz and colleagues identified five highly predictive indicators of dropout: attendance rate less than 80% of the time during 6th grade, failed 6th grade mathematics, failed 6th grade English, one or more out-of-school suspensions, and a final unsatisfactory behavior grade in any subject during 6th grade. Although each of these indicators alone were predictive of dropout, the odds of dropping out significantly increased with each additional flag that the student acquired, regardless of the combination of variables. For example, a student who had an F in both 6th grade English and 6th grade mathematics was at a greater risk of dropping out of school when compared to a student who only had an F in mathematics Balfanz and colleagues found students with one flag had a graduation rate of 36%, while those with two, three, and four flags had a graduation rate of 21%, 13%, and 7%, respectively. Similar research has corroborated these findings, which suggest that the number of risk factors is a more robust predictor of negative outcomes, compared to any one risk factor alone (e.g., Coie et al., 1993; Heppen, & Therriault, 2008; Jerald, 2006a).

Researchers from the Baltimore Education Research Consortium (2011) corroborated Balfanz and colleagues (2007) findings that suggest middle school data is pertinent information to include in an EWS. The Baltimore Education Research Consortium found the following early warning indicators for 6th graders to be highly predictive of dropout: 1) chronic absences (i.e., missing 20 or more days of school during an academic school year); 2) failing English and/or mathematics and a failing average for English, mathematics science, and social studies; 3) being at least one year over age (which the researchers argued suggested earlier grade retention); and 4) being suspended for three or more days. Students who were chronically absent in 6th grade had a 29% likelihood of graduating within one year of their expected graduation year, and the more instructional time students missed the less likely they were to graduate (e.g., students who missed more than 40 days had a 13% chance of graduating). The Baltimore Education Research Consortium also found that having multiple indicators greatly reduced the probability of graduation. For example, students with a single indicator had a 50% likelihood of graduating within one year of original graduation year, while those with two, three, and four indicators had a graduation likelihood of 26%, 13%, and 8%, respectively.

To further extend the literature on the complex process of dropping out of high school, Bowers (2010) applied survival analysis using discrete-time hazard techniques to a longitudinal data set, which included grade histories for grades 1-12 from two high schools. Bowers (2010) found that dropout risk factors did not emerge until 7^{th} grade, and the largest portion of dropouts left school in the 11^{th} grade. This means that until grade 7, there was a zero percent probability, for this dataset, that a student would leave school prior to graduation, but at 7^{th} grade the probability rose to 2.6%. Bowers (2010) found that the risk of dropping out continues to increase over the subsequent years, leveling off from 8^{th}-10th grades to approximately 4%, and then peaking dramatically at 11^{th} grade to 9.4%. While the majority of students dropped out in 11^{th} grade, 12^{th} grade was not exempt from dropout. Similar to the rates documented in 8^{th}–10^{th} grade, approximately 3.5% of students dropped out in 12^{th} grade in Bowers' sample. Again, Bowers' (2010) research highlights the importance of the middle school years in the process of dropping out.

Influenced by Balfanz and colleagues work from 2011 the NHSC modified their EWS Excel© template to include indicators for middle school performance and behavior (National High School Center, 2012). The middle school indicators that were included were attendance, English course failure, mathematics course failure, and a locally defined behavioral indicator. The criterion to flag students for attendance was set at missing 20% or more of instructional time during the first 30 days of each semester. Course failures were defined as earning an end of year grade of an F in either mathematics or English. The NHSC recommend that local data be used to operationally define the behavioral indicator. Schools can choose to set the behavior threshold based on locally defined classroom behavior grades, office referrals, or out-of-school suspensions depending on what data is readily available within the district. Like the previous version of the Excel® template, the EWS Middle Grades program can be downloaded for free from the National High School Center's website. Additionally, the *National High School Center Early Warning System Middle Grades Tool Technical Manual* (2012) and *Middle Grades Early Warning Intervention Monitoring System Implementation Guide (2013)* provides district administrators detailed procedures on how to implement and incorporate this tool into their larger dropout prevention and intervention initiatives.

Higher Education. Leaving school prior to graduation is a phenomenon that extends beyond secondary school and permeates higher education as well. Although college enrollment rates among U.S. colleges and universities is on the rise (NCES, 2016), gaps in degree attainment continue to pervade institutions of higher education (Arnold, Lu, & Armstrong, 2012). For the past twenty years, the college dropout rate has remained stagnant at a rate of 20-25% (Bowen, Chingos, & McPherson, 2009; Hudson, 2006; Vaysberg & Fagan, 2015). While the average national college dropout rate has remained stagnant, it is important to note that college retention and graduation rates vary greatly be institution type (Aud et al., 2011).

Like their secondary school counterparts, institutions of higher education have implemented centralized systems that flag students who are at-risk of leaving college prior to obtaining their degree (Bowen, Price, Llyod, & Thomas, 2005; Fischman, 2007; Hanover Research Council, 2014; Tampke, 2013). In higher education these systems are often referred to as early *alert* systems rather than early *warning* systems (Jayapraskash, Moody, Lauria, Regan, & Baron, 2014; Hanover Research Council, 2014). Approximately 94% of America's four-year colleges and universities report implementing an early alert system (Barefoot, Griffin, & Koch, 2012). Similar dropout indicators used in high school EWS are also present in early alert systems used at institutions of higher education, including attendance, grades, and aptitude test scores (Hanover Research Council, 2014; Hudson, 2006; Jayapraskash et al., 2014; Wood, 2011).

Advocates of early alert systems in higher education argue that students fall through the cracks when colleges and universities do not have centralized processes and systems in place that evaluates student performance throughout a semester (Hanover Research Council, 2014; Wood, 2011). While most colleges and universities offer student support services such as career counseling, tutoring, and mentoring, without an early alert system, institutions would have to wait until after a student has failed one semester to refer students to these services. Implementing an early alert system that tracks student performance, primarily measured by grades, attendance, completion of homework, and/or classroom engagement, throughout the semester provides timely information on students who are falling off-track to faculty and staff (Wood, 2011). When faculty and staff have access to timely data about which students are at-risk they can offer resources and guidance to help students get back on-track.

Empirical evidence suggests that an early alert system is an effective system for institutions of higher education to increase student retention rates. For example, to increase student success, an early alert system focused on monitoring chronic absenteeism coupled with intrusive advising (e.g., proactive advising strategies that include mandated advising sessions) was implemented at Eastern Kentucky University. Hudson (2006) found the early alert system was an effective method to increase communication between academic advisors and students, which resulted in a significant reduction in the number of students who would have failed courses due to a lack of attendance.

To add to the early alert system outcome literature, Tampke (2013) examined the relationship between using early alert system data and student outcomes. In 2008, the Early Alert Referral System (EARS) was implemented at the University of North Texas, Denton. During the initial term of use, Tampke (2013) found that 87 faculty members had referred 255 students from 108 courses using the institutions newly implemented early alert system. Results indicated that referred students who were successfully contacted by faculty or support service personnel had higher term GPAs compared to referred students who did not receive personal contact.

While the indicator variables used in higher education's early alert systems are similar to indicators used in secondary school's EWS, it is important to note that higher education early alert systems only include data reflective of postsecondary performance and attendance, and these systems do not include retrospective data from high school.

Summary. Research clearly demonstrates that dropout risk factors are prominent throughout the educational system, spanning across elementary grades to postsecondary institutions (e.g., Allensworth & Easton, 2005; Balfanz et al., 2007; Alexander et al., 1997; Hudson, 2006). Interestingly, across each of these educational time periods, similar risk factors continually emerge, such as attendance and course performance as measured by course grades. While research has identified a set of core EWS variables (i.e., attendance, behavior, and course grades), a unique feature of the EWS tool is the degree of flexibility it can afford districts and postsecondary institutions. The next section briefly outlines how districts and postsecondary institutions can build an EWS specifically tailored to the needs of their student population.

Efficacy of the Key Early Warning System Indicators

Relatively speaking, the EWS is a fairly new tool educators can use to predict and, hopefully, prevent dropout. Decades of research identifying key indicators of dropout paved the way for the development of this tool and have provided the foundational framework for EWSs (e.g., Coley, 1995; Finn, 1993; Roderick, 1993, 1994; Roderick & Camburn, 1999). Throughout the dropout literature, four main risk factors continually emerge, which include academic achievement, absenteeism, grade-level retention, and family socioeconomic status (Barrington & Hendricks, 1989; Finn, 1989; Rumberger, 1987, 1995, 2004; Alexander et al., 2001; Allensworth & Easton, 2005, 2007; Balfanz et al., 2007; Pinkus, 2008). Unfortunately, research has found the predictive validity of these risk factors on high school dropout to be moderately low (Dynarski & Gleason, 2002). The following section attempts to shed light on the efficacy of the EWS indicators by reviewing studies that examine the sensitivity, specificity, and precision of key EWS indicator variables.

In a comprehensive review of the literature, Bowers, Sprott, and Taff (2013) investigated the precision, sensitivity, and specificity of dropout flags cited in the high school dropout prediction literature over the past 30 years. In this review, Bowers and colleagues (2013) examined 36 articles, which identified 110 dropout flags, that met the following inclusion criteria: (a) The study focused on high school dropout prediction; (b) The study examined school-wide characteristics, all students in the school were included in the study and was not specific to a subgroup of students (e.g., students with a learning disability); (c) The study focused on student-level, not school-level, dropout characteristics; (d) The study contained quantitative data that fit requirements for recalculating precision, sensitivity, and specificity. Precision was defined as the true-positives divided by the total number of students with the flag, sensitivity is the true-positives divided by the total number of actual dropouts, specificity was operationalized as the true-negatives divided by the total number of graduates, and the false-positive proportion was defined as the false-positives divided by the total number of graduates. None of the studies reviewed reported all four of these metrics of accuracy, with most studies only reporting on precision. Precision rates for dropout flags varied widely across the 36 studies, with a low of .041 for a student employment variable, to a high of .971 for a flag composed of a combination of risk-factors including mother's education level, single parent family, and grade-level retention (Bowers et al., 2013). Similarly, the sensitivity and specificity rates were mixed across the dropout flags. For example, the sensitivity rates ranged from a low of .047 for the mobility flag and a high of .969 for the flag that captured student involvement in at least one high school extracurricular activity; specificity rates ranged from a low of .184 for the flag that conveys student involvement in at least one middle school extracurricular activity and a high of .999 for a flag composed of a combination of risk-factors including mother's education level, single parent family, and grade-level retention (Bowers et al., 2013). Bowers and colleagues found studies that utilized growth mixture modeling techniques produced the most accurate flags. Variables that included longitudinal data on mathematics achievement, non-cumulative semester GPA, and engagement from grades 7-12 were the most accurate predictors of dropout, with mathematics achievement as the most accurate flag.

The development and refinement of the EWS has largely occurred in heavily urbanized contexts, such as Chicago, Philadelphia, New York, and Baltimore (Allensworth & Easton, 2005; 2007; Curran Neild, 2009; Jerald, 2006b; Heppen & Therriault, 2008). To investigate the predictive validity of the EWS indicators within less populous areas, Johnson and Semmelroth (2010) conducted a cross-validation study using data from two suburban high schools in the

Northwest. Johnson and Semmelroth (2010) examined the classification accuracy, sensitivity, specificity, and risk estimates of the EWS used within the target districts. The risk estimate compares the probability of an outcome in each group, which is the risk of dropping out for a student with and without the indicator present. Similar to previous research (Dynarski & Gleason, 2002), Johnson and Semmelroth (2010) found the combination of highly predictive indicators (absenteeism rate, course failures, GPA, and on-track indicator) produced acceptable levels of sensitivity (i.e., levels that are greater than .80), but only moderate levels of specificity (i.e., levels between .50 and .80). For example, the sensitivity of the combination of variables was .95 and 1.00 in High School 1 and High School 2, respectively; and the specificity was .75 and .64, respectively. These results suggest that the EWS slightly over-identified students as at-risk. When the variables were examined individually, GPA was the strongest predictor of dropout in both high schools; however, research has clearly demonstrated that no single indicator can perfectly predict dropout (Bowers et al., 2013; Johnson & Semmelroth; Gleason & Dynarski, 2002). Prediction is more accurate when multiple indicator variables are included (Freeman & Simonsen, 2015; Curran Neild, 2009; Suh & Suh, 2007) and data is examined using longitudinal research methodologies and analytic techniques (Bowers et al., 2013).

Drawing on empirical evidence that suggests longitudinal research methodologies are the most robust way to examine student's academic trajectories (Carl et al., 2013; Curran Neild, 2009; Curran Neild et al., 2007; Bowers et al., 2013; Johnson & Semmelroth, 2010), the current study extends this body of research beyond high school outcomes (i.e., high school graduation). The current study examines longitudinal data on student achievement and engagement as measured by middle and high school EWS variables in predicting postsecondary outcomes (i.e., immediate enrollment and persistence). Examining achievement and engagement data through a longitudinal lens is a vehicle for exploring and identifying sensitive time points, where students may be especially vulnerable to dropping out, or in the case of the current study, falling off-track on the path to college readiness.

Summary of Early Warning Systems in Secondary Schools

To answer the call to action to increase high school graduation rates (Obama, 2009), school districts have espoused innovative methods to identify and serve at-risk students. A paramount result of these efforts has been the ubiquitous adoption of the EWS designed to identify and flag students who are at-risk of dropping out of school prior to graduation (Allensworth & Easton, 2007; Bafanz et al., 2007; Davis et al., 2013; Dynarski, et al., 2008; Frazelle, & Nagel, 2015; Kennelly & Monrad, 2007; Knowles, 2015; Heppen & Therriault, 2008; Jerald, 2006a). The EWS literature suggests that district administrators should examine local extant data to inform the creation of their EWS to ensure that the most prominent dropout variables are included (Jerald, 2006a, 2006b; Pinkus, 2008). Heeding current research trends and recommendations from the dropout literature, school districts can incorporate an EWS into their dropout intervention and planning initiatives to increase the number of students who remain in school and on-track for a high school diploma. Further, to extend student's success beyond high school, districts can incorporate the research findings from the EWS into their college and career readiness initiatives. The next section outlines how dropout EWS can be modified to include germane information on student's level of college and career readiness.

Extending Early Warning Systems Beyond High School Graduation

While preventing high school dropout is a critical step to ensuring student success, in today's 21st century workforce, a high school diploma is not enough. It has been projected that by the year 2020, approximately 63% of jobs nationwide will require postsecondary education for an entry-level position (Georgetown University Center on Education, 2013). To help facilitate a successful transition to postsecondary education and careers, school districts must provide students with a solid educational foundation. Just as the EWS provides pertinent information on student's risk of dropping out of high school, this tool may be able to serve a dual purpose and provide similar information regarding student's college readiness.

To maintain a competitive edge within the global economy, the United States' workforce must produce and consist of highly skilled and trained workers. To fulfill these requirements, it is critical that today's students attain education beyond high school. According to the National Center for Education Statistics (NCES, 2016), enrollment in degree-granting postsecondary institutions has increased by 20%, from 16.9 million to 20.4 million between 2003 and 2013. A plausible explanation for the increased enrollment rates may be related to population growth. Between 2003 and 2013, the number of 18 to 24 year-olds increased from 28.9 million to 31.5 million (NCES, 2016). While population growth likely contributes to the increased enrollment trends, another likely factor related to this increase is the shift in college aspirations among high school students, which have doubled, from 40% of students indicating they hope to obtain a bachelor's degree in 1980 to 80% in 2002 (Roderick, 2006).

While there is evidence of increased enrollment rates among high school graduates (e.g., NCES, 2016), research has also found that a large portion, approximately 10-25%, of students who aspire to attend college do not actually show up at the postsecondary institution in the fall semester following graduation (Castleman & Paige, 2013; Castleman, Paige, & Schooley, 2013). A recent report by the Bureau of Labor Statistics (2015) revealed that only 68% of high school graduates immediately enrolled in colleges or universities during the fall semester following high school graduation. This rate is consistent with previously reported postsecondary enrollment rates. In 2003, Greene and Foster reported that 70% of all public high school graduates entered college following high school graduation. For students who do choose to enroll in a postsecondary institution, the degree completion rate is relatively low. Symonds, Schwartz, and Ferguson (2011) found that only 30% of young adults who attend college immediately following high school earn a bachelor's degree by their mid-twenties, which translates into degree completion within six years. Similarly, among a sample of nationally representative students who began postsecondary education in 2003-04, 49% earned a postsecondary credential, ranging from an educational certificate to a bachelor's degree by 2009 (NCES, 2010). The slightly higher rate reported by the NCES (2010) is likely caused by differences in inclusion criteria. NCES included educational certificates as part of the outcome, whereas Symonds and colleagues (2011) study only examined bachelor degree attainment. With an increasing demand for postsecondary credentials in the national workforce these stagnant rates are very concerning (Bureau of Labor Statistics, 2015; Greene & Foster, 2003).

Many of the students who do enter a postsecondary institution upon high school graduation are academically underprepared. According to ACT (2015), only 40% of high school graduates who took the ACT test in 2015 attained a college-ready score, as measured by the ACT college-readiness benchmarks. Up to 60% of students attending nonselective colleges and universities met their institutions' eligibility criteria, but were not ready for college-level course work (Arnold et al., 2012). While highly selective colleges (i.e., Harvard University, Yale University, Stanford University, etc.) have a much lower percentage of incoming students who are unprepared (approximately one in ten), these institutions are not exempt from this issue (Arnold et al., 2012). The large portion of freshman students, approximately 20-30%, who are placed into non-credit bearing remedial or developmental courses at public, four-year colleges provides evidence that students lack the necessary academic preparation to succeed in entry-level coursework in college (Greene & Forster, 2003; NCES, 2013). This is very problematic for universities and colleges, as remedial course work is closely linked to reduced rates of retention and degree completion (Arnold et al., 2012).

There is clearly a need to improve postsecondary preparedness and success. To help increase the college readiness of students, secondary schools must be aware of the variables that predict eventual postsecondary success. Policymakers and educational advocates have encouraged districts to expand the scope of the EWS, and begin to explore the potential of using indicators embedded in the EWS that are available in high school or middle school as potential measures of college readiness (Data Quality Campaign, 2013; Durham, Bell-Ellwanger, Connolly, Robinson, Olson, & Rone, 2015; Kemple et al., 2013; Mishook, 2012a; Phillips, et al., 2015; Roderick, Nagaoka, & Coca, 2009).

College Readiness. During the 21st century, the term "college and career readiness" has become an omnipresent mantra echoed throughout the halls of the American educational system (McAlister & Meys, 2012). Unfortunately, politicians and educational leaders often overlook the career readiness portion of this buzz phrase, and place a larger emphasis on preparing students to be college ready upon high school graduation (Barnes & Slate, 2013; Barnes, Slate, & Rojas-LeBouef, 2010). As a result of this localized emphasis, the current study exclusively focuses on college readiness and the literature that surrounds it.

Over the years, educational researchers, policymakers, and practitioners have addressed and discussed the transition process from high school to college using several different terms, including *college choice*, *college access*, and *college preparation* (Arnold et al., 2012). While the majority of these terms touch on a piece of the college transition process, they do not capture the multidimensional set of skills necessary to enter and succeed in college. Educational researchers, policymakers, and practitioners have embraced a more general term that addresses a wider range of skills needed to enter and succeed in college, *college readiness* (Arnold et al., 2012).

What does it mean for a student to be "college ready"? Broadly speaking, a student must first graduate from high school and pass specific high school courses that are designated as college ready courses required for college admissions (Greene & Forster, 2003). Further, college readiness encompasses students' practical knowledge to engage in college search activities, as well as the aspirations, motivations, and self-efficacy to attend college (Arnold et al., 2012). More specifically, college readiness refers to a student who can qualify for and succeed in entry-level, *credit-bearing* college courses that will lead to a baccalaureate or certificate, without the need for developmental or remedial coursework (ACT, 2008; Arnold et al., 2012; Conley, 2008, 2011; Conley, McClary, & Larson, 2013). Durham and colleagues (2015) argue that the most parsimonious definition of college readiness rests on the notion that high schools have sufficiently prepared students academically, and there is not a need for the student to enroll in remedial courses to further build their foundational skills. To further operationalize this concept, state leaders and educational policymakers developed the college-ready standards as part of the Common Core State Standards Initiative (CCSSI). The CCSSI is a blueprint proposal that specifies that college-ready students are students who have completed a rigorous elementary and secondary academic program in English language arts and mathematics (McAlister & Meys, 2012). While each of the previously mentioned definitions captures what it means to be college ready, it is important to note that college readiness is a complicated phenomenon rooted in the complex interactions of societal ideology, organizational structures, and individual agencies, and researchers should be cognizant that when they study only one aspect, college preparation, a restricted view of college readiness is produced (Arnold et al., 2012).

Unfortunately, there are disparities among racial groups with regard to college readiness status (Bryant, 2015; Dougherty, 2010; Roderick, Coca, & Nagaoka, 2011). For example, research has found that Black and Hispanic students are significantly underrepresented in the pool of minimally qualified college applicants, as only 9% of all college-ready applicants were Black and only 9% were Hispanic, compared to the total student population for these two groups: 14% Black and 17% Hispanic (Greene & Forster, 2003). Similar discrepancies are found across SES groups as well. A substantially higher percentage of high-income (79%) students enroll in college immediately following high school graduation compared to middle (64%) and low (52%) income students (Roderick et al., 2009). To mitigate these discrepancies, Mishook (2012b) advocates for a comprehensive approach to college-readiness that involves both in- and out-of-school educational opportunities and supports.

Drawing on previous work in the field of college readiness (e.g., Callan, Finney, Krist, Usdan, & Venezia, 2006; Arnold et al., 2012; Conley, 2005; 2008; Roderick et al., 2009; Zhao, 2009), researchers from the Annenberg Institute for School Reform at Brown University, the John W. Gardner Center at Stanford University, and the Consortium on Chicago School Research at the University of Chicago in accompaniment with five urban districts (Dallas Independent School District, Pittsburgh Public School District, San Jose Unified School District, Philadelphia Public School District, and New York City Public School District) developed the College Readiness Indicator System (CRIS) to further expand the concept of college readiness. The CRIS framework contains three college readiness dimensions, including academic preparedness, academic tenacity, and college knowledge (Borsato, Nagaoka, & Foley, 2013;

McAlister & Meys, 2012). The academic preparedness domain refers to key academic content knowledge (measured by GPA and ACT/SAT score) needed to succeed in college-level coursework. Academic tenacity refers to the underlying beliefs and attitudes that drive student achievement, measured by attendance and behavioral data. Finally, college knowledge refers to student's ability to navigate the nuances of college, including the financial requirements for college (Borsato et al., 2013; Gurantz & Borsato, 2012). Within the CRIS framework, college knowledge is often measured by completion rates of key pre-college activities, including successful completion of college and financial aid applications and the number college visits a student takes. College knowledge can also be assessed using locally developed self-report surveys that assess the student's perception of the college-going culture within the school and/or district (Borsato et al., 2013).

The CRIS framework recognizes that the responsibility of providing college readiness resources extends beyond the school district, which is why this framework also includes a "Cycle of Inquiry" that districts can utilize to mobilize community partners (Annenberg Institute for School Reform, John W. Gardner Center for Youth and their Communities, & Consortium on Chicago School Research, 2014). The Cycle of Inquiry encourages districts to explore the local and state political contexts around college readiness in order to map out the conditions for each key indicator (Annenberg Institute of School Reform et al., 2014). For example, school districts should evaluate whether local graduation requirements are rigorous enough to prepare students to meet admissions requirements for competitive higher education institutions.

In their *College Readiness Guide*, McAlister and Meys (2012) outline strategies and interventions to bolster skills within each area of college readiness. For the academic preparedness college readiness domain, early intervention informed by data is recommended with special attention focused on the transition from middle to high school (i.e., *Talent Development Model* or the *Early College High School Initiative*). This recommendation directly aligns with the dropout literature (e.g., Allensowrth & Easton, 2005; Curran Neild et al., 2007), which suggests that an EWS may be a beneficial tool within the realm of college readiness. Strategies within the academic tenacity domain include activities designed to increase self-awareness, meta-cognition, self-control, organization, and critical thinking skills (i.e., *Advancement Via Individual Determination Program* or *TRIO* programs). Finally, the college knowledge domain focuses on increasing student's awareness and understanding of how to get in and pay for college; strategies within this domain include building a college-going culture within the school district (i.e., *Knowledge is Power Program Through College* or *Say Yes to Education* programs). Within the CRIS framework, the EWS used for dropout detection could be altered to flag students at-risk of falling off-track for college readiness.

College Readiness Indicators. A rich body of research has identified variables associated with college readiness (e.g., ACT 2008; 2015, Becker et al., 2014; Belfield & Crosta, 2012; Cromwell, McClarty, & Larson, 2013; Kemple et al., 2013; Kless, Soland, & Santiago, 2013; Lee, 2012; Lotkowski, Robbins, & Noeth, 2004; Roderick et al., 2009; Zhao & Liu, 2011). Throughout this literature, several key variables continually emerge as significant predictors of postsecondary success, including high school GPA, performance on college entrance exams, and high school course selection.

GPA. Research has consistently found that high school GPAs are useful for predicting many aspects of students' college performance (ACT, 2015; Becker et al., 2014; Belfield & Crosta, 2012; Carl et al., 2013; Kless et al., 2013; Lavorini, 2013; Lotkowski et al., 2004; MacIver & Messel, 2013; Noble & Sawyer, 2002). Becker and colleagues (2014) found that 9th

grade GPA was a significant predictor of postsecondary enrollment in the fall semester immediately following high school graduation. A weighted high school GPA greater than 2.00 has also been linked to higher enrollment rates immediately following high school graduation (Durham et al., 2015). Similarly, researchers from ACT found that maintaining a cumulative high school GPA of at least a 3.00 was significantly correlated with success in entry-level college courses, defined as a C or higher in the course (ACT, 2015). Carl and colleagues (2013) found that high school graduates with a core, cumulative GPA less than a D average (i.e., 1.00 GPA), had on-time college enrollment rates less than 10%, despite being technically "on-track" for high school graduation.

High school GPA has been found to account for approximately 30% of the variance in first-year college GPA (Korbin, Patterson, Shaw, Matten, & Barbuti, 2008). High school GPA also has a strong association with college credit accumulation, with higher cumulative high school GPA related to higher rates of credit accumulation per semester (Belfield & Crosta, 2012). Finally, in an extensive study of over 75,000 University of California students, Geiser and Santelices (2007) found that high school GPA was consistently the strongest predictor of four-year college outcomes for all academic disciplines, and the predicative validity of this variable increased the longer the student was in college. Specifically, Geiser and Santelices (2007) found that cumulative high school GPA accounted for 26.7% of the variance of cumulative fourth-year GPA (i.e., college senior status), and 24.5% of the variance of first-year GPA (i.e., college freshman status). Other studies have corroborated this finding that high school GPA is the strongest predictor of postsecondary outcomes (ACT, 2015; Noble & Sawyer, 2002; Roderick et al., 2009).

While research has substantiated the importance of high school GPA on predicting postsecondary success (e.g., Becker et al., 2014; Belfield & Crosta, 2012; Carl et al., 2013; Korbin et al., 2008; MacIver & Messel, 2013), this variable is not without limitations. It has been noted within the educational research literature that using GPA as an indicator of postsecondary success poses problems because this variable is a composite of grades, which often fails to account for course rigor, grade inflation, or changes in grading standards (Davis, 2010; Kless et al., 2013). Further, GPA is less predictive of college success for students who achieve very low grades (Kless et al., 2013).

College entrance exams. Performance on college entrance exams (i.e., ACT and SAT) is another key variable used to predict postsecondary success. Research has found that higher ACT and SAT scores are positively correlated with postsecondary enrollment trends (Conley, 2008; Kless et al., 2013; Roderick, 2006). Meeting college readiness benchmarks on college entrance exams (defined as a 21 composite for the ACT or a combined reading and mathematics score of at least 990 on the SAT) significantly predicted postsecondary enrollment immediately following high school graduation (ACT, 2015; Becker et al., 2014; Bettinger & Long, 2005; Cromwell et al., 2013). Additionally, meeting these benchmark standards on both the ACT and SAT have been linked to higher first-year GPAs in college (Cromwell et al., 2013; Bettinger & Long, 2005; Radunzel & Noble, 2012). Students who met ACT benchmarks on each section of the exam (i.e., English, Reading, Mathematics, and Science) were more likely to persist into their second year of college compared to students who did not meet college readiness benchmarks (Cromwell et al., 2013; Radunzel & Noble, 2012). Finally, students who met or exceeded benchmarks on the SAT were almost two times more likely to graduate in four years compared to students who did not meet the benchmark (Mattern, Shaw, & Marini, 2013).

Research clearly indicates that performance on college entrance exams is a strong predictor of first-year college success; unfortunately, this variable is less predictive of later college success (Kless et al., 2013). Geiser and Santelices (2007), for example, found performance on college entrance exams was a weaker predictor of postsecondary persistence and college grades compared to other high school predictor variables, particularly high school GPA, after controlling for SES. Similarly, Lotkowski and colleagues (2004) found high school GPA (r = .25) and SES (r = .23) had a stronger correlation with college persistence compared to ACT assessment scores (r = .12). Lotkowski (2004) also reported that high school GPA was a stronger predictor of college GPA (r = .45) compared to ACT scores (r = .39) and SES (r = .16). Another limitation to using college entrance tests as a predictor of postsecondary success is that the assessments are often not directly aligned with states' content standards (Davis, 2010). Further, college readiness benchmarks that are used on the ACT and SAT are set above the national median score, which means that these benchmarks are "above grade level" (Dougherty, 2010).

High school courses. Finally, high school course selection has been linked to future academic success in college. Students who complete a core curriculum (i.e., four years of English, three years of mathematics, three years of science, and three years of social studies), a mathematics course beyond Algebra II, and enrolled in at least one advanced course are more successful in college than students who do not elect to take these courses (Cromwell, 2013; Bryant, 2015; Radunzel & Noble, 2012).

Researchers and educators alike often refer to mathematics as a gatekeeper for future educational opportunities (Byun, Irvin, & Bell, 2015). It is likely that mathematics is referred to as a gatekeeper because research has shown that mathematics achievement and ability is associated with several other educational outcomes including standardized test scores, high school completion, college performance, and postsecondary degree completion (e.g., Attewell & Domina, 2008; Byun et al., 2015; Gaertner, Kim, DesJardins, & McClary, 2014; Geiser & Santelices, 2007; Long, Iatarola, & Conger, 2009; Wiley, Wyatt, & Camara, 2010; Wyatt, Wiley, Camara, & Proestler, 2011). To examine the impact of mathematics enrollment on postsecondary outcomes, Adelman (2006) examined data from two cohorts of students from the High School and Beyond (HSB) dataset and the National Education Longitudinal Study of 1988/2000 (NELS: 88/2000) dataset. The HSB dataset examined outcomes for the graduating class of 1982 and the NELS:88/2000 dataset examined outcomes for the graduating class of 1992. Adelman (2006) found students in the HSB dataset who enrolled in Algebra II or higher were more likely to earn a postsecondary degree than students in this dataset who did not enroll in an advanced mathematics course. Interestingly, for the later cohort of graduates studied in the NELS:88/2000 dataset, Adelman (2006) found enrollment in Trigonometry or higher became the margin for postsecondary degree attainment.

While Adelman's (2006) study provides key insights into the importance of mathematics enrollment in predicting postsecondary outcomes, the majority of research investigating the impact of course taking on student outcomes has been criticized for nonrandom selection of students into different curricular paths (Gaertner et al., 2014). To address this criticism, Byun and colleagues (2015) employed propensity score matching (PSM) techniques to examine the impact of mathematics course taking behavior on college enrollment. Byun and colleagues (2015) examined data from a national representative sample using data from the Educational Longitudinal Study of 2002-2006 (ELS:02/06). Results revealed that students who enrolled in an advanced mathematics course, defined as enrollment in at least one course beyond Algebra II, were approximately two times more likely to be enrolled in college than students who did not complete an advanced mathematics course, regardless of SES or race/ethnicity.

Another area of course taking behavior that has been linked to future college success is enrolling and succeeding in advanced courses. Specifically, enrollment in advanced placement (AP), international baccalaureate (IB), and/or dual-credit (DC) courses has been identified in the literature as strong predictors of postsecondary outcomes. For example, Becker and colleagues (2014) found enrollment in at least one AP, IB, or DC course significantly predicted four-year postsecondary enrollment, but was not a significant predictor of two-year college enrollment. This likely indicates that students who enroll in these advance courses are not selecting two-year institutions as their source of postsecondary education, but rather are opting to enroll in a four-year college or university instead. While simply enrolling in an AP, IB, or DC course increases a student's likelihood of enrolling in college upon completion of high school, research has also found that performance in these courses is predictive of college success. Students who scored a 3 or higher on at least one AP high school exam were significantly more likely to enroll in postsecondary intuitions compared with students who obtained lower scores on the exam (Zhao & Liu, 2011). Similarly, Leonard (2010) found students who entered college with postsecondary credits earned by successfully passing the AP exam were less likely to need remediation.

Like the other college readiness predictors, there are limitations and challenges with using course selection as a measure of college readiness. For example, the availability of AP courses varies widely across school districts and is often related to school-wide SES, with lower SES schools offering fewer, if any, AP courses (Mishook, 2012b). Further, research has found significant gaps in the share of underrepresented students, including low-income and minority students, who take AP courses. In 2003-04, only 16% of high school graduates of low SES completed an AP course compared to 51% of high SES graduates; additionally, only 16% of Black students and 25% of Hispanic students took an AP course in high school compared with 33% of White students (Roderick et al., 2009).

The variables identified through this robust body of research provide school districts a foundational base to use predictive analytics to study student success and college readiness (Becker, et al., 2014). Although school districts have a large amount of data that is readily available, they often feel overwhelmed with the task of harnessing relevant data that can easily be translated into actionable initiatives and interventions. Including too many data elements into an EWS can be cumbersome and confusing for district staff (University of Chicago Consortium on Chicago School Research, 2014). Therefore, just as it was recommended for EWS focused on preventing dropout behavior, an EWS with a dual focus of college readiness should be informed by local data to identify the variables that matter most to their student population (Jerald, 2006a; Durham et al., 2015; University of Chicago Consortium on Chicago School Research, 2014).

The current study will incorporate findings from this body of research as a means to identify key predictor variables (e.g., GPA, standardized assessment scores) to include in the analytic models. This study will also harness relevant data that the partnering school district can utilize to inform program planning efforts to increase their student's college readiness.

Integration of Early Warning Systems into the College Readiness Initiative

With an increasing focus on college readiness, researchers have begun to explore the potential for incorporating college readiness into the EWS structure. Unfortunately, a dearth of information is available on the efficacy of the integration of these two frameworks, as very few published studies have included postsecondary measures as outcomes in the predictive analyses of early warning indicators. An extensive review of the EWS literature revealed only two studies that included a postsecondary measure as an outcome variable: Becker and colleagues (2014) and Soland (2013).

In conjunction with Dallas Public School (DPS) districts, research fellows from Harvard's Strategic Data Project conducted extensive analyses of the early warning indicators used in DPS. As part of their analyses, Becker and colleagues (2011) examined postsecondary success as an outcome variable. Postsecondary success was defined as enrolling in a two- or four-year institution in the fall semester immediately following high school graduation. All of the outcome variables were obtained from data provided from the National Student Clearinghouse (NSC). The early warning indicators that were used in the prediction model included 9^{th} grade GPA, 9^{th} grade on-track status (as defined by Allensworth & Easton, 2007), attendance rate, PSAT college readiness benchmark, Destination 2020 benchmark for SAT/ACT (ACT composite higher than 21 and combined reading and mathematics SAT of at least 990), enrollment in AP/IB/DC courses, and enrollment in career and technical education courses. Becker and colleagues (2014) found their model containing all early warning indicators was the strongest predictor of enrollment in four-year colleges and universities. Further, Becker and colleagues found grades and attendance data consistently predicted postsecondary enrollment for all three outcomes, college enrollment overall, enrollment in a four-year colleges, and enrollment in two-year colleges. Meeting the Destination 2020 benchmarks on the ACT and/or SAT were the strongest predictors for enrollment in four-year institutions, but less predictive for enrollment in two-year colleges.

Soland (2013) also used a measure of college readiness in his study comparing teacher intuition and EWS predictions of whether students will graduate from high school and enroll in college. The study sought to investigate whether an EWS enhances the precision with which at-risk students are identified, or whether these tools were primarily a conversation starter about information teachers already know. To address this question, Soland used data from the National Education Longitudinal Study (NELS), selecting variables often found in EWSs including data on absences, suspensions, average 8th and 9th grade GPA, standardized reading and mathematics scores in 8th grade (i.e., standardized tests developed by NELS), course failures in English, mathematics, social studies, or science, AP enrollment, enrollment in Geometry or Algebra, and a grade-level retention (i.e., if the student was ever held back). Teacher predictions of graduation and college enrollment were obtained when students were in 10th grade. Similar to Becker and colleagues (2014), Soland (2013) defined his college readiness measure as immediately enrolling in college the fall semester following high school graduation. Soland (2013) found EWS produced more accurate predictions of college enrollment than teacher predictions. Further, EWS identified more students who were on the cusp of being at-risk than teacher prediction. That is, teachers were able to predict students who were severely at-risk of dropping out; however, teacher predictions were less accurate for students with less pronounced risk. However, in Soland's study, the EWS variables were limited to early high school snapshots of time, 8th through 10th grades. Further, college enrollment was reported via self-reports from the students rather than actual enrollment records.

Measures of Postsecondary Success

Colloquially speaking, postsecondary success is most often associated with degree completion. However, a closer examination of this seemingly simple outcome reveals a complex variable that warrants further unpacking to arrive at an operational definition. Trend analysis in higher education focuses on three broad categories of postsecondary success: enrollment, persistence, and graduation rates (Adelman, 2006). The most definitive measure of postsecondary success is degree completion; unfortunately, linking middle and high school indicators to an outcome so far in the future poses several challenges, including timely data analysis to impact programming and interventions (Cromwell et al., 2013). When researchers opt to use degree completion they must allow adequate time for students to complete the degree, which usually means a four to six year delay. To overcome these challenges, researchers can utilize earlier postsecondary milestones and accomplishments that predict degree completion as a proxy measurement (Adelman, 2006).

One of the most common proxy measures for postsecondary degree completion is enrollment in college immediately following high school graduation. The higher education literature has found students who forgo enrollment in a postsecondary institution immediately following high school graduation are less likely to complete and secure a postsecondary credential or degree (Horn, Cataldi, Sikora, & Carroll, 2005). Persistence is another commonly used proxy measure for degree completion. Research has also found that the majority of students who drop out of college do so within the first two semesters of college (Geiser & Santelices, 2007). It is important to note that persistent rates have also been linked to the selectivity of the postsecondary institution. For example, institutions that have an open enrollment policy (that is they accept 100% of students who apply) have been found to have a 57% retention rate, while highly selective institutions (that accept less than 25% of applications) had retention rates of 95% (Aud et al., 2011). Drawing on findings from the research literature, researchers often use enrollment in a postsecondary institution immediately following high school graduation and postsecondary persistence, which is defined as continuous enrollment in at least two semesters, as proxy variables for degree completion (Cromwell et al., 2015; Kuh, 2007; Kuh, Kinzie, Buckley, Bridges, & Hayek, 2007).

Summary and Limitations of the Literature

Research has demonstrated support for both middle and high school EWS's impact on reducing drop out by identifying at-risk students based on a core set of indicators, including attendance, behavior, and course failures (Allensworth & Easton, 2007; Curran Neild et al., 2007; Jerald, 2006a, 2006b). However, there are still gaps within this literature. Specifically, little is known about the utility of these systems in predicting postsecondary outcomes, as very few studies have examined this outcome. Of the studies available that have begun to examine EWS's impact on postsecondary outcomes, the majority of the focus is centered on early warning indicators at snapshots in time. For example, Becker and colleagues (2014) used a snapshot of academic data from 9th grade (i.e., GPA and on-track status) and 11th grade (i.e., ACT/SAT scores), rather than examining student's dynamic longitudinal academic performance over time. In addition to the limited scope of academic performance, Becker and colleagues (2014) did not include behavioral data (e.g., suspensions) as predictor variables, which has been found in the dropout literature to be an important early warning indicator (e.g., Allensworth & Easton, 2007; Balfanz et al., 2007). Similar limitations were noted in Soland's (2013) study. Soland's (2013) study focused on academic data from 8th-10th grade, which fails to capture the longitudinal impact of early warning data at later grades. Both Becker and colleagues (2014) and Soland's (2013) studies examined a narrow scope of postsecondary success, as both studies only examined the impact of early warning indicators on enrollment trends immediately following high school graduation.

The present study will seek to extend this body of research in three ways. First, the present study will examine the impact of early warning indicators through a longitudinal lens. Acknowledging the longitudinal nature of student's academic decisions and trajectories (i.e., graduating high school and/or enrolling in college) highlights the need for studies to apply rigorous data analyses that produce models capable of capturing the variables and time periods most predictive of student success. Second, this study will also contribute to the EWS research literature by exploring the predictive validity of early warning indicators on postsecondary persistence. Third, this study will expand the literature on college readiness by examining the predictive validity of high school attendance rates and high school behavioral incidents on postsecondary outcomes (i.e., college enrollment and persistence). Finally, the vast majority of research conducted with EWSs has occurred within the context of large urban districts (e.g., Chicago, New York, Baltimore, Dallas, and Philadelphia). The current study will use data provided by one moderately sized district within the Midwestern United States. This study will provide local validity data for the partnering school district, as well as offer external validity for similar, less urban school districts with regard to the predicative validity of key EWS indicator variables on predicting postsecondary outcomes.

Research Questions and Hypotheses

The following research questions and hypotheses guided this study:

Question 1. What is the temporal relationship between the key EWS variables (i.e., attendance, behavior, course grades, and standardized assessment performance)?

- Hypothesis 1: There will be a significant temporal relationship among each of the key EWS variables. That is, statistically significant autoregressive effects will be present for each of the four main EWS variables: attendance, behavior, course grades, and standardized assessment performance.

Question 2. Which key EWS variables are significantly related to postsecondary enrollment?

- Hypothesis 2: Based on the review of literature, the following key EWS variables are hypothesized to be statistically significantly related to postsecondary enrollment immediately following high school graduation: 12^{th} grade GPA, 12^{th} grade attendance, 12^{th} grade behavioral referrals, 9^{th} grade GPA, and 7^{th} grade GPA.

Question 3. Which key EWS variables are significantly related to postsecondary persistence?

- Hypothesis 3: Based on the review of literature, the following key EWS variables are hypothesized to be statistically significantly related to postsecondary persistence: 12^{th} grade GPA, 12^{th} grade attendance, 9^{th} grade GPA, and 7^{th} grade GPA.

Chapter III

Methods

This study was designed to investigate the utility of Early Warning System (EWS) indicators commonly used for dropout prevention in secondary schools as key predictors of postsecondary enrollment and persistence. Data from one moderately sized Midwestern school district was used to predict postsecondary enrollment outcomes, including initial postsecondary enrollment the fall semester immediately following high school graduation and persistence in a postsecondary institution for at least six semesters. This chapter describes the study's participants, procedures, variables, research design, and analytic plan.

Participants and Procedures

Five school districts were solicited to participate in this study. Four of the school districts were located in northeast Kansas and one of the school districts was located in south central Kansas. Two school districts agreed to participate in the study and three school districts declined due to limited staff resources needed to construct the data files. After committing to participating in this study, one of the partnering school districts discovered they no longer had access to individual-level postsecondary enrollment data for their students. Efforts were made to secure funding for this district to purchase a license with the National Student Clearinghouse (NSC) to obtain postsecondary data, however, funding was not secured and the district did not have the financial resources necessary to obtain a NSC license. Because individual student-level postsecondary data was unavailable for this district, and final analyses could not be conducted without this information, data from only one partnering school district is included in the final sample.

Student-level data for the graduating class of 2013 was solicited from the partnering school district and the following criteria were applied for inclusion in the study's sample: students who were members of the 2007-2008, 7th grade cohort, with an original, on-time graduation year of 2013. For the purpose of this study, on-time graduation was defined as graduating within 4 years of starting high school. To capture the student's academic trajectory starting in middle school, data for this cohort of students was tracked forward from 7th grade through 12th grade. The final sample consisted of 3,078 students from the partnering school district. See Appendix A, Figure 1 for a graphic representation of the participant selection process.

The partnering school district provided seven individual data files, one file per academic year for secondary school (e.g., 7th grade, 8th grade, etc.) and one NSC file containing six semesters of postsecondary outcomes (i.e., data from 2013 – 2016). Each of these files contained the information necessary to construct a longitudinal data file to capture students' academic trajectories across both secondary and postsecondary education. At the partnering school district students are assigned unique student identification numbers that are used to link student records together across academic school years and track outcomes. For the purposes of this study, de-identified student-level information was requested to protect student anonymity and comply with Family Educational Rights and Privacy Act (FERPA) regulations. To protect student anonymity and still ensure that records could be linked over time, the partnering school district applied a unique study-related identification number to each student record within the seven data files prior to distributing the files to the researcher. After applying the study-related identification number, the partnering school district removed all personally identifiable information from the files including student's name, birth date, and state and school identification numbers.

Ethical Considerations

As part of responsible scholarship, researchers must consider and address potential ethical issues. Primary ethical issues that needed to be managed in the present study included participant confidentiality and the protection of sensitive, personally identifying information (PII). To minimize this risk, the researcher requested de-identified student-level data. As described above, the school district removed all PII including, student names, birth dates, and school and state identification numbers prior to releasing the files to the researcher. Additionally, the school district created a unique student identification number that was different from their school-based identification number. Finally, all the files received from the partnering school district were stored on a secure, password-protected computer that only the researcher and university advisor could access. The removal of individual identifiers and secure storage of data files reduced the risk of breaches of confidentiality, thus ensuring that confidentiality was maintained. Approval from the University of Kansas Human Subjects Committee of Lawrence (HSCL) was secured for this study (See Appendix B). As per this approval, an exemption of informed consent was granted. Because this study relies on retrospective data, obtaining consent from each participant would have been impractical for a number of reasons, including the extensive amount of time it would take to contact each participant and secure consent. In addition to the IRB approval, formal approval was secured from the partnering school district. The formal data request outlined the specific variables needed for this study, as well as security measures to protect student information and ensure FERPA compliance.

Construction of Data File

To construct the longitudinal file, data from each school year was tracked forward beginning with the 2007-2008 school year when the cohort students were in 7th grade. Prior to combining the data files, each individual academic year file was checked for data quality. In each academic year file duplicate student records were identified and removed. There were 26 duplicate records in the 2007-2008 (7^{th} grade) file; 28 duplicate records in the 2008-2009 (8^{th} grade) file; 25 duplicate records in the 2009-2010 (9^{th} grade) file; 25 duplicate records in the 2010-2011 (10^{th} grade) file; 17 duplicate records in the 2011-2012 (11^{th} grade) file; and 8 duplicate records in the 2012-2013 (12^{th} grade) file. Additionally, students who were retained at any point during the 7^{th}-12^{th} grade years were removed from the sample because they no longer met criteria for cohort membership (i.e., original graduation year of 2013). Although repeating a grade at any point during school can be a significant risk factor for dropout and college enrollment (e.g., Jimerson, 1999; Jimerson, Anderson, & Whipple, 2002; Roderick, 1994; Roderick et al., 2009; Rumberger, 1995), including this variable in the model would make the data collection and analyses overwhelmingly complex because students may repeat grades at different time points and this would require multiple years of outcome data.

After removing duplicate records and students who repeated a grade, data from each subsequent academic year was merged with the 2007-2008 file. Table 1 provides an overview of the construction of the longitudinal file and an overview of the final sample utilized in this study. In Table 1, the column labeled *Unique Student Records* refers to the number of individual student records found in each academic year file. The column titled *Number of Students who were Continuously Enrolled* refers to students who had been previously enrolled in the district at least once during a previous school year. The column labeled *Number of Students who Transferred In* refers to students who were new to the district in that academic year. Finally, the column titled *Number of Students who Transferred Out* refers to the number of students who left the district during that academic year.

Table 1. Overview of the longitudinal file construction.

	# Unique Records	# Students Continuously Enrolled	# Students Transferred In	# Students Transferred Out
7th Grade	2179	--	--	--
8th Grade	2142	1993	149	186
9th Grade	2347	1987	360	178
10th Grade	2147	1984	163	380
11th Grade	2058	1945	113	247
12th Grade	2099	1985	114	150

Previous research indicates that student mobility is a major concern for urban school districts. On average, approximately 20-30% of urban school district students change schools at least one time during the academic year (Kerbow, 1996; Rumberger, 2015). As demonstrated in Table 1, mobility issues were a concern for this study as well. On average, each year approximately 19% of students in the sample transferred in or out of the partnering school district. For the current study, several rules were applied to address the mobility concern. First, if a student transferred schools within the district, they were retained in the sample because their academic data continued to be tracked and monitored at the district level. These students were coded as being continuously enrolled in the district. Second, to address student mobility in terms of students transferring into the district from out of district, the research plan allowed new students into the cohort as they transferred into the district. Data that was not available for transfer students from previous years was treated as missing data. To control for the effects of student mobility, a mobility covariate variable was included in the model. A thorough description of the mobility variable is provided below. Table 2 provides an overview of the demographic composition of the study's sample.

Table 2. *Demographic overview of the study's sample*.

Variable	N	Percentage
Gender		
Male	1486	48%
Female	1592	52%
Race/Ethnicity		
White	2121	69%
Black	356	12%
Hispanic	413	13%
Asian	73	2%
Other	115	4%
Free/Reduced Lunch Status		
Yes	1094	36%
No	1984	65%
Students with Disabilities		
Yes	303	10%
No	2775	90%
Students Identified as Gifted		
Yes	214	7%
No	2864	93%
English Language Learner Status		
Yes	279	9%
No	2799	91%
Mobility		
Yes	1594	48%
No	1484	52%
Total number of participants	3078	

Variables

Previous research has identified a core set of variables related to on-track graduation, including attendance, behavior, and academic achievement (e.g., Allensworth & Easton, 2007; Christle, Jolivette, & Nelson, 2007; Dynarski et al., 2008). The EWS variables utilized in this study included data on each of the core indicators. Table 3 provides an overview of the variables utilized in this study and the following section provides a description of the predictor and outcome variables. Prior to running analyses all variables were checked for data quality and appropriate data cleaning procedures were implemented when necessary (Tabachnick & Fidell, 2007). A full description of the data cleaning procedures is provided in the Results section.

Predictor Variables. Student-level data on attendance rates, behavioral incidents, state assessment results, and non-cumulative GPA were obtained from the partnering school district. These variables were used as the independent variables in the analyses.

Attendance Rates. Yearly attendance rates for the targeted six years was tracked and collected from students within this cohort each year they were enrolled in the partnering school district. Yearly attendance rate was calculated as a percentage by dividing the total number of days a student was present by the total number of days the student was enrolled in the partnering school district. Preliminary data cleaning procedures indicated that the attendance variables were severely negatively skewed. To better approximate normality, a reflected logarithmic transformation was applied to each of the attendance variables (Tabachnick & Fidell, 2007). A full description of the transformation is provided in the Results section.

***Behavioral Incidents*.** Data on the number of office referrals (ODRs) that were entered into the district wide discipline system was tracked for the target six years. There have been debates within the general education literature on the external validity of ODRs (cf. Spaulding et al., 2010; Predy, McIntosh, & Frank, 2014), as a number of factors including teacher tolerance and school policy can influence the systematic collection of this variable. However, Predy and colleagues (2014) indicate that when ODRs are systematically collected and tracked this variable is an accurate measure of student behavior. In light of these mixed results, it was deemed appropriate to include this variable in the present study's model, as it has been found to be predictive of dropout behavior (e.g., Balfanz et al., 2007; Curran Neild & Balfanz, 2006). Preliminary data cleaning procedures revealed that the behavioral incidents variables were severely positively skewed. To better approximate normality, a logarithmic transformation was applied to each of the behavioral incidents variables (Tabachnick & Fidell, 2007). A full description of the transformation is provided in the Results section.

State Assessment. Grade-level standardized state assessments were given in the spring semesters during cohort students' middle and high school years. During middle school, cohort students took the state assessment in the spring semesters in both 7^{th} and 8^{th} grades. During high school, students were only required to take the state assessment one time. While the majority of students took the state assessment in 10^{th} grade during high school (81%), some students completed the assessment in 9^{th}, 11^{th}, or 12^{th} grades. State assessments measure student's achievement in English language arts and mathematics. During the time students took the state assessment, scores were divided into five categories based on the student's percent correct on the test: academic warning, approaching standards, meets standards, exceeds standards, and exemplary. For this study, the descriptive categories were coded according to the following guidelines: 1= academic warning; 2 = approaching standards; 3= meets standards; 4 = exceeds standards; 5 = exemplary. Preliminary analyses indicated that students' state assessment performance on the English language arts and mathematics subtests in middle school were highly correlated ($r = .989$, $p < .001$). Similar results were found with students' performance across the two areas in high school as well ($r = .947$, $p < .001$). To account for this multicollinearity, separate mean state assessment performance scores were calculated for cohort students' middle and high school performances by averaging the student's middle and high school performances across English language arts and mathematics assessments, respectively. The correlation among the resulting middle and high school state assessment variables was not as highly correlated as the within time reading and mathematics correlations ($r = .805$, $p < .001$).

GPA. Previous research has demonstrated that non-cumulative GPA for each academic year is an effective predictor of high school graduation (e.g., Bowers, 2010), as well as postsecondary enrollment and persistence (e.g., ACT, 2015; Becker et al., 2014; Belfield & Crosta, 2012; Carl et al., 2013). Therefore, GPA was not aggregated across years, but rather was calculated on a four-point scale for each year. Calculations were made using the following weights: An “A” grade was weighted with four points, a “B” grade was weighted as three points, a “C” grade was weighted as two points, a “D” grade was given a one point weight, and an “F” grade was weighted as zero points. Mean non-cumulative GPA for each grade level was calculated by averaging the mean GPA for all subjects within each grade level. Additionally, GPA was included in this model to capture student achievement across a broad range of areas. In contrast to the previously described state assessment indicator, which measures student performance in only two areas (i.e., mathematics and language arts) the non-cumulative GPA measure captures student achievement across core subjects (e.g., mathematics, science, social studies) and also electives (e.g., art, music, etc.). Finally, the GPA indicator captures academic achievement that is specific to each target year, rather than more general academic skills that tend to be captured by state assessments.

Outcome variables. Postsecondary outcomes were used as the dependent variables in the analyses. This data was provided directly from the partnering school district. The partnering school district has a private contract with the NSC, who systematically collects postsecondary enrollment status data from more than 3,500 colleges and universities in the United States (e.g., full-time, half-time, less than half-time, withdrawn, begin and end dates, schools attended, type of school). The schools represented in the NSC database enroll 98% of students attending public and private nonprofit postsecondary institutions across the United States (Newbaker, 2014).

The outcome variables that were used in this study focused on postsecondary enrollment patterns. To answer the previous listed research questions two outcome variables were created, one that reflected initial enrollment in a postsecondary institution and another that reflected continuous enrollment in a postsecondary institution among participants. Specifically, an enrollment outcome variable was created that captured whether or not cohort students immediately enrolled in a postsecondary institution during the fall 2013 semester following high school graduation. A second outcome variable was created that measured students' persistence in college. Previous research has utilized persistence as a proxy measure for postsecondary graduation (e.g., Adelman, 2006; Geiser and Santelices, 2007). The persistence variable used in this study measured continuous enrollment in at least six semesters, or graduation with a certificate or two-year postsecondary degree. Students did not need to be continuously enrolled at the same college to be coded as persisting, but rather maintain continuous enrollment at any postsecondary institution. The two outcome variables are described in detail below.

Postsecondary Enrollment. The postsecondary enrollment variable was coded as 0 (did not enroll in a postsecondary institution immediately following high school graduation) and 1 (enrolled in a postsecondary institution immediately following high school graduation). Students who did not enroll in a postsecondary institution during the fall semester immediately following graduation (i.e., fall 2013) were coded as not enrolling (n = 209). It was anticipated that some students would not attend a postsecondary institution immediately following graduation, but would eventually attend at a later date (Castleman & Page, 2013). The current study is primarily concerned with immediate enrollment and persistence in postsecondary education, and to keep the model parsimonious, postsecondary enrollment for students not immediately enrolled were coded as a 0, which represents that they did not enroll immediately. Approximately 65% of the sample enrolled in a postsecondary institution immediately following high school gradation, and 35% did not immediately enroll.

Postsecondary Persistence. Persistence was defined as continuous enrollment in at least six semesters (fall 2013, spring 2013, fall 2014, spring 2015, fall 2015, and spring 2016). Students who persisted for at least six semesters at a postsecondary institution were coded as 1 and students who did not persist for all six semesters were coded as 0. Students who attended a 2-year institution or a technical college were afforded the opportunity to graduate with a 2-year degree or a certificate without enrolling in six complete semesters. To account for this opportunity, students who graduated with a 2-year degree or certificate within the allotted timeframe were also coded as 1 (n = 92). Since the persistence variable is being used as a proxy for postsecondary graduation, earning a 2-year degree or credential was equated as a similar successful outcome as persisting in six semesters. Again, the researcher anticipated that some students would not continuously persist for all six semesters immediately following high school graduation, but may leave college for a period of time and return at a later date. Students who did not have continuous postsecondary enrollment data for all six semesters were coded as 0, which indicated that they did not persist. Approximately 47% of the sample persisted in at least 6 semesters immediately following high school graduation or secured a 2-year degree or credential, whereas 53% of the sample did not persist.

Covariates. General student demographic data including gender, race, English Language Learner (ELL) status, free and reduced lunch status (FRL), and special education status (SPED) were solicited for the targeted six years (i.e., 7^{th} - 12^{th} grade). These variables were used as covariates to help control for the effects of demographic variables on postsecondary enrollment trends. Demographic variables tend to remain relatively stable over time, although there may be some error with data entry or changes in status (e.g., exit from ELL or SPED). The time point at which each variable was coded is described below.

Gender. Gender was operationalized as a dichotomous variable, male or female, as self-reported on the demographic form completed and submitted to the partnering district at the beginning of each school year. Students who identified as male were coded as 1 and students who identified as female were coded as 0. The first time point in which the student was enrolled in the district was used to code gender. Gender data from other time points was examined for consistency to ensure data quality. Gender was perfectly correlated across years (r = 1.00). This suggests that the same gender category was consistently reported for students across each of the target six years (i.e., 7^{th} – 12^{th} grades).

Race. The district-wide estimates of race for the partnering school district utilized the reporting method outlined by the State Department of Education (i.e., White, Black, Asian, Hispanic, and Other). Race was self-reported on the demographic form completed and submitted to the partnering district at the beginning of each school year. Because the statistical software that was utilized for this study does not allow covariates to be specified as nominal or categorical, it was necessary to dummy code these variables and treat them as continuous (Muthén, 2009; Muthén & Muthén, 1998-2011, p. 488-489). To accommodate this issue, the race variable was dichotomized, and students who identified as White were coded as 0 and students who identified as any other race were coded as 1. The first time point in which the student was enrolled in the district was used to code for race. Race data from other time points was examined for consistency to ensure data quality. The correlation among the race variable slightly varied across years, r ranged from .85 to 1.00. This finding suggests that overall race was consistently reported for students across each of the target six years.

Free/Reduced Lunch Status. As defined by the guidelines set forth by the National School Lunch Program (NSLP), students from families with incomes at or below 130 percent of the poverty level are eligible for free meals; and students from families with incomes between 130 and 185 of the poverty level are eligible for reduced-priced meals, for which students can be charged no more than 40 cents (United States Department of Agriculture, 2015). Free and Reduced Lunch (FRL) status was solicited from the partnering school district and represents those students who opted into the program. If a student met the criteria for FRL status at any point during the target six years they were coded as a student who met the criteria for FRL. Students who did not qualify for the FRL program or did not opt into the program were coded as 0. Students who did qualify for the FRL program and opted in were coded as 1.

Special Education Status. Special education (SPED) services are specially designed educational services provided to students with unique learning needs that adversely affect the child's performance in the general education classroom. There are thirteen categories that students can qualify for special education services under the Individuals with Disabilities Education Improvement Act (IDEA, 2004). If a student met the criteria for SPED services at any point during the six years, they were coded as a student who met the criteria for SPED. For the purpose of this study students who were not in SPED were coded as 0 and students who were identified and received SPED services at any point during the target six years data were available were coded as 1.

Gifted Education Status. Gifted education services are specifically designed educational services for students who demonstrate evidence of high levels of achievement capabilities in areas such as cognitive and academic functioning and require additional educational supports to fully develop those capabilities. In the partnering school district students are identified for gifted services through the district's multidisciplinary Student Intervention Teams. If a student met the criteria for gifted services at any point during the target six years they were coded as a student who met criteria for gifted education. For the purpose of this study gifted status was coded as 0 = did not receive gifted services and 1 = received gifted services if the student had been coded by the partnering school district as receiving gifted services at any point during the target six years data was available.

English Language Learner Status. English Language Learner (ELL) status refers to students who are active learners of the English language who may benefit from supplemental language support programs. If a student meets the criteria for ELL status at any point during the target six years they were coded as a student who met criteria for ELL services. ELL status was coded as 0 = does not receive ELL services and 1 = has received ELL if the student had been coded by the partnering school district as receiving ELL services at any point during the target six years data was available.

Mobility. Students who transferred into the partnering school districts at any time during the target years (i.e., 7^{th} – 12^{th} grade) were included in the study sample. To control for the associated effects of mobility (i.e., Rumburger & Laron, 1988; Rumberger, 2003), students who transferred into or out of the district at any time during the target years were coded as 1. Students who were continuously enrolled at the partnering school district for all of the target school years were coded as 0.

Table 3 provides an overview of the coding methodology applied to each of the variables used in the study.

Table 3. *Variable coding*

Variables	Coding Methodology	Coding Value	Time Point
Outcome Variable			
Enrollment	Enrollment patterns were coded for the two possible enrollment conditions	0 = Did not enroll 1 = Immediately enrolled	Fall 2013
Persistence	Persistence patterns were coded for the two possible persistence conditions	0 = Did not persist 1 = Continuously persisted for at least 6 semesters or earned a degree/credential	Fall 2013 – Spring 2016
Predictor Variables			
Attendance Rates	Number of days present divided by total number of days per year	Percentage	$7^{th} – 12^{th}$ grade
Behavioral Referrals	Total number of ODR's recorded in discipline system each year	Total Number	$7^{th} – 12^{th}$ grade
State Assessment	State standing categories based on standard scores	1 = warning 2 = approaching 3= meets 4 = exceeds 5 = exemplary	Middle School & High School
Grade Point Average	Average end of year, non-cumulative GPA across subjects	Average	$7^{th} – 12^{th}$ grade
Covariates Variables			
Gender	Dummy coding of self-reported gender status	0 = Male 1 = Female	First time point enrolled
Race	Dummy coding of race	0 = White 1 = Non-White	First time point enrolled
Free/Reduced Lunch (FRL)	Dummy coding of FRL status	0 = Not FRL 1 = FRL	Coded FRL if meets criteria at any time point
Special Education Status (SPED)	Dummy coding of SPED status	0 = Not SPED 1 = SPED	Coded SPED if meets criteria at any time point
Gifted Education Status	Dummy coding of Gifted status	0 = Not Gifted 1 = Gifted	Coded Gifted if meets criteria at any time point
English Language Learner (ELL)	Dummy coding of ELL stats	0 = Not ELL 1 = ELL	Coded ELL if meets criteria at any time point
Mobility	Dummy coding of transfer status,	0 = Did not transfer	$7^{h} – 12^{th}$ grade

Variables	Coding Methodology	Coding Value	Time Point
	which captures transfer status at any point during 7th-12th grade	1 = Transfer	

Missing Data

Longitudinal studies provide researchers a unique opportunity to examine the impact of growth over time (Palmer & Royall, 2010). While this type of research provides a comprehensive examination of outcomes and how a variety of variables impact those outcomes over time, longitudinal studies are not without challenges. One of the most significant challenges to longitudinal studies is the presence of missing data due to attrition of study participants (Frees, 2006; Little, 2013; Young & Johnson, 2015). Attrition can be problematic as it may result in selection bias, which can have a significant impact on parameter estimates in regression models (Frees, 2006; Little, 2013). For example, participants who transferred in or out of the partnering school district prior to graduation may be different than students who completed grades 7-12th in the same school district. To address selection basis and maximize the generalizability of the result of this this study, patterns of missing data were examined and appropriate statistical techniques were applied to handle the missing data.

Missing data can be classified into one of three categories: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). The classification system used to define missing data influences the optimal strategy researchers should apply for dealing with missing values within their dataset (Acock, 2005). When data are MCAR the probability of missing data on one variable is unrelated to the other variables within the dataset; that is, the data that is missing is entirely unsystematic (Baraldi & Enders, 2010; Little, 2013). This assumption can be specifically tested using Little's test for MCAR (Enders, 2010; Little, 1988). The MAR classification refers to missing data that is systematically related to other variables that are included in the study; that is, the missing data is related to other variables that are included in the analysis, but because those other variables are included in the analysis this can account for missing data and parameter estimates are not biased (Acock, 2005; Baraldi & Enders, 2010; Little, 2013). Finally, MNAR refers to data that are missing as a result of the variable itself (Baraldi & Enders, 2010; Little, 2013). For example, a student who has poor reading skills may have missing data on a reading assessment because the student could not finish the test.

There are several methods available to handle and adjust for missing data. Historically, the default method to dealing with missing data was to exclude observations with missing data from the analysis using listwise or pairwise deletion methods (Palmer & Royall, 2010). Listwise deletion methods drop cases where there is missing data on any of the variables used in the analysis, whereas pairwise deletion techniques remove incomplete cases only from analysis that include the variable with missing values (Roth, 1994). Unfortunately, there are several disadvantages to relying on these traditional techniques including a loss of power and biased parameter estimates, which increase the likelihood of committing a Type II error (failing to detect an effect that is present; Palmer & Royall, 2010; Roth, 1994). Further, these traditional methods rely on the assumption that the data is MCAR, which is rarely the case in applied research (Baraldi & Enders, 2010).

As statistical techniques evolved, superior alternative methods were developed to handle missing data. Currently, maximum likelihood (ML) estimation and multiple imputation (MI) methods are considered the “state of the art” missing data techniques (Baraldi & Enders, 2010; Schafer & Graham, 2002). The primary benefit to these two methods is that they do not delete cases or variables with missing data, but rather uses all of the information provided to estimate the model parameters that best reflect the sample data (Baraldi & Enders, 2010; Little, 2013). Specifically, ML computes a series of parameter estimates that would likely be produced by the data, and the estimate with the highest probability is used (Keith, 2006). Structural equation models (SEM), including path models, tend to use ML as the default for dealing with missing data (Keith, 2006).

While patterns of missing data are difficult to formally test, specifically testing for MAR and NMAR patterns, safeguards are built in to the model to minimize the impact of missingness. To minimize the impact of missing data within the study's sample, covariates were included in the model. Including covariates into the model increases the likelihood that the sample results obtained in this study will be accurate estimates of the true population parameters. For example, including the covariate for mobility provides information on both students who move in as well as students who move out of the partnering school district. In other words, the population of students who are mobile may be different than students who are not mobile, and by including covariates to help account for this it can help account for missing data and meet the requirements for MAR.

Research Design

To answer the previously stated research questions, a non-experimental, retrospective cohort research design, was employed. Since the focus of this study design is retrospective in nature, secondary analyses of extant data were conducted. A multivariate cross-lagged panel model was used to examine the longitudinal effects of EWS indicators on postsecondary outcomes. Figure 1 in Appendix A depicts a graphic representation of the study design (Kanchanaraska, 2008). This design is referred to as a *causal-comparative design* because it attempts to investigate the outcome of interest by retrospectively examining differences in variables that potentially influence the outcome (Peers, 2006).

Analytic Plan

The present study utilized path analysis to analyze all data. Path analysis is an extension of multiple regression and considered the simplest form of structural equation modeling (SEM, Keith, 2006). Path analysis is a multivariate technique that tests relationships among measured variables. Path models are an appropriate analytic technique for this study for a number of reasons. First, while path analysis and multiple regression may appear to do the same thing (i.e., analyzing the relationship between a criterion variable and a set of predictor variables), path analysis is a more robust analytic technique because it simultaneously analyzes the impact of multiple variables, which can include a combination of one or more variables on the criterion variable (Finkel, 1995). Further, path analysis is a primary method for examining patterns of correlations among key variables identified by the researcher's underlying theory to draw casual inferences about the data (Keith, 2006; Vogt, 2005). For this study, previous research suggests that attendance, behavioral incidents, state assessment scores, and GPA across grade levels will be highly correlated across time (e.g., Allensworth & Easton, 2007). Because of the anticipated correlations, path analysis was selected as the statistical technique to examine the data. The data analysis procedures occurred through multiple steps including creating a tentative model that outlines the relationships among the key variables, estimating the model, reporting model estimates, and testing competing models using the goodness of fit test (Keith, 2006; Winship & Mare, 1983). All path analyses were performed using Mplus 6 (Muthén & Muthén, 1998-2011). A comprehensive description of the model specification procedures is described below.

Preliminary Model Specification. The preliminary statistical analyses for this study involved specifying the multivariate cross-lagged panel model that would be used to estimate the impact of the key EWS variables on postsecondary outcomes. These preliminary analyses were also used to address the research Question 1. The first step to defining the cross-lagged panel model was to estimate the relationships among the key EWS variables across the target six years by examining autoregressive effects. Autoregressive effects allow the researcher to examine the degree of stability of variables over time (Geiser, 2013). To examine the autoregressive effects, each EWS variable (i.e., attendance, behavioral incidents, GPA, and state assessment scores) was regressed on the same variable from the previous year. For example, GPA from 12th grade was regressed on GPA from 11th grade, and GPA from 11th grade was regressed on GPA from 10th grade, and so on. This process was conducted for each of the variables included in the model.

The second step in the preliminary analysis included estimating the correlations among the residuals of the key EWS variables within each academic year. For example, correlations were estimated among the residual variance of the key EWS variables in 7th grade, where GPA, attendance, behavioral incidents, and state assessment were all correlated with each other. This was applied to each successive academic year (i.e., 8th – 12th grades). Residual correlations among the key EWS variables within each year were included in the model to account for shared occasion-specific effects (Geiser, 2013).

The third step in the preliminary analysis involved adding cross-lagged paths into the model. Cross-lagged paths allow the researcher to examine the effects of additional, temporally preceding variables that are included in the model (Geiser, 2013). More specifically, cross-lagged regression parameters provide information on how much variation in one variable at an earlier time point is able to predict the change in the other variables within the model at subsequent time points (Berrington, Smith, & Sturgis, 2006). Because cross-lagged models operate under the assumption that previous behavior is the best predictor of present or future behavior (Geiser, 2013), several plausible cross-lagged paths were tested. Based on previous research and theory (e.g., Alexander et al., 2001; Balfanz, 2009; Baltimore Education Research Consortium, 2011; Bowers, 2010; Carl et al., 2013; Ensminger & Slusarcick, 1992; Freeman & Simonsen, 2015; Predy et al., 2014) it was hypothesized that individual differences in GPA, attendance, and behavioral incidents would be influenced by temporally preceding behaviors and scores on the other variables. Specifically, it was hypothesized that previous year's GPA would predict future behavioral incidents, previous year's GPA would predict future attendance, and finally previous year attendance would predict future GPA. The first series of cross-lagged paths included in the model measured the impact of previous year's GPA on the following year's behavioral incidents were added (e.g., 8^{th} grade GPA was regressed on 7^{th} grade behavioral incidents). Similar cross-lagged paths were included for each successive grade level. The second series of cross-lagged paths that were included in the model estimated previous year's GPA on the following year's attendance rates (e.g., 8^{th} grade GPA was regressed on 7^{th} grade attendance). Again, similar cross-lagged paths were included for each successive grade level. Finally, cross-lagged paths that accounted for the influence of previous year's attendance rates on the following year's GPA were added (e.g., 8^{th} grade attendance was regressed on 7^{th} grade GPA).

The fourth and final step in the preliminary analysis included adding the covariates to the multivariate cross-lagged panel model. To estimate the impact of individual-level student information, covariates were added to the model defined in previous steps. Covariates that were included in this model were either binary (i.e., nominal) or categorical. In Mplus, only dependent variables can be specified as either NOMINAL or CATEGORICAL, and these options should not be used for covariates (Muthén, 2009; Muthén & Muthén, 1998-2011, pp. 488-489). Therefore, covariates included in the model were dummy coded and treated as continuous. Because several covariates included in this study were believed to remain stable over time (i.e., gender, ethnicity), or were coded in such a way to eliminate temporal change (i.e., FRL, IEP, ELL), covariates were regressed on only one time point (i.e., 7^{th} grade). Only regressing the covariates onto 7^{th} grade EWS variables helped to keep the overall cross-lagged panel model parsimonious. Modification indices were examined to determine if there were any specific effects from covariates on later time points.

Figure 2 depicts the basic cross-lagged panel model (i.e., path diagram) that was used to define the hypothesized relationships among the key EWS variables and covariates identified and supported by theory and previous research (e.g., Allensworth & Easton, 2007; Christle et al., 2007; Dynarski et al., 2008). The basic multivariate cross-lagged panel model includes four predictor variables that occur over six years (attendance, behavioral incidents, GPA, and state assessment results) and seven covariates (gender, race, FRL, SPED, gifted, ELL, and mobility). All of the predictor variables in the model are continuous variables, and the covariates in the model are dichotomous (i.e., gender, ELL status, race, SPED status, gifted status, and mobility status). The path model was a recursive path model, which means that paths (presumed causes) are unidirectional (Keith, 2006).

Final Model Specification. After defining the basic multivariate cross-lagged panel model, which included an estimation of the relationship among the key EWS variables and the covariates, primary analyses were conducted to address the study's research questions examining postsecondary outcomes (research Questions 2 and 3). Because the study's primary research questions focused on both postsecondary enrollment and postsecondary persistence as outcomes, separate analyses were completed for each outcome. Similar to the process utilized in the preliminary analyses, a series of steps designed to elucidate which EWS variables were related to postsecondary outcomes and at which times point was conducted. Primarily, a series of nested model comparisons using the χ^2 difference test were conducted to determine which model parameters had statistically significant impacts on the outcomes of interest, postsecondary enrollment and persistence (Little, 2013).

A series of models were estimated where predictors from each previous grade were entered into the model one grade level at a time. The first model estimated the impact of 12th grade EWS variables on the outcome. The second model estimated the impact of 11th grade EWS variables on the outcome, the third model estimated the impact of 10th grade EWS variables on the outcome, and so on until the 7th grade variables were included in the model. The series of nested models were designed to identify and estimate which EWS had statistically significant impacts on postsecondary outcomes, and at which time point. Direct paths were estimated for each of the key EWS variables (i.e., attendance, behavioral incidents, GPA, and state assessment performance) across the target six years for each of the postsecondary outcomes. EWS variables from each grade level were sequentially regressed on the postsecondary outcome of interest (i.e., enrollment or persistence) beginning with EWS variables from 12th grade. Direct effects were examined, and non-statistically significant paths were removed from the model. Specifically, the path with largest non-statistically significant value (determined by examining *p* values) was removed first, and then the model was re-estimated. If additional non-statistically significant paths remained, the next largest non-statistically significant path was removed, and the model was re-estimated. This process occurred until only statistically significant paths remained. Once a model with only statistically significant direct paths for 12th grade was established, the same process was repeated for each of the remaining grade levels in reverse order (i.e., 11^{th} – 7^{th}). The reduced models were re-fitted after each successive modification. The final model contained only statistically significant structural paths for each of the EWS variables across the six target years. For this study an alpha level of .05 was selected as the critical level.

Model Estimation. A fundamental component of SEM is specifying model parameters. There are two types of parameters used in SEM: fixed parameters and free parameters (Fields, 2009). Fixed parameters are typically set to 0, which indicate no relation between variables; and free parameters indicate the presence of a relationship between variables and are estimated from the data. Direct and indirect effects within in the model were specified. Direct effects refer to the sensitivity of a dependent variable to changes in the independent variable while all other factors in the analysis are held constant (Pearl, 2011). Indirect effects assess the effect of a proposed cause on some outcome through a proposed mediator variable (Preacher & Hayes, 2004).

Once the models were constructed, estimates of the free parameters were obtained from the set of observed data. Since the outcomes of interest for the primary research questions were dichotomous (i.e., enrolled vs. did not enroll and persisted vs. did not persist) nonlinear regression techniques were used to estimate the direct effects of variables in the outcome models (Goodman, 1972; Winship & Mare 1983). In Mplus, the default nonlinear regression technique for a binary outcome is a probit regression model and the default estimator for this type of analysis is robust weighted least squares (Muthén & Muthén, 1998-2011, p. 25; Muthén, 2005).

According to Muthén (2005) the probit regression model is a more general model than the logit regression model for binary dependent variables. Probit regression models transform the binary nature of the dependent variable into a normal distribution using a cumulative normal distribution function, where the inverse standard normal distribution of the probability is modeled as a linear combination of predictors (Muthén, 1998-2004; Nagler, 1994; UCLA Statistical Consulting Group, 2017). In a probit model, the value of X*b* is taken to be a *z*-value of a normal distribution, where higher positive values indicate that the event is more likely to happen (O'Halloran, 2017). In other words, the probit regression coefficients represent the change in the *z*-score (probit index) for one unit change in the predictor (UCLA Statistical Consulting Group, 2017). The regression coefficients that are produced by a probit regression model capture how much the conditional probability of the outcome variable changes when there is a one unit change in the value of the predictor variable, while holding all other predictor variables constant (Long, 1997; Muthén, 1998-2004; Nagler, 1994). In addition to the probit coefficients (i.e., standardized [β] and unstandardized [*b*] estimates) that are produced from a probit model, the output also provides thresholds, which are equivalent to intercepts in linear regression models, except the thresholds in a probit model have the opposite sign than would be expected from an intercept (UCLA Statistical Consulting Group, 2017; Long, 1997).

An additional nonlinear regression technique that could be applied is the logit regression technique. In Mplus this nonlinear technique utilizes the maximum likelihood with robust standard errors (MLR), which helps account for multivariate nonnormality in data (Gesier, 2013). There have been claims within the field that the MLR estimator is a superior estimation technique compared to the weighted least squares estimator (Mehrota, Kulkarni, Tripat, & Michale, 2000). However, other scholars have found that both estimation techniques produce similar results and there is no gain in efficiency when one method is selected over the other (Withers & Nadarajah, 2012). The maximum likelihood estimator technique is an iterative procedure that attempts to maximize the likelihood that obtained values of the outcome variable will be accurately predicted (Wuensch, 2016). Unfortunately, the output provided by Mplus for a logit regression model does not include appropriate fit indices that can be used to compare competing, nested models (e.g., χ^2, CFI, RMSEA). Because a primary procedure of this study included a model comparison across each respective academic year, the probit regression techniques were selected and utilized to estimate the impact of the EWS variables across target years. Research indicates that probit and logit regression models produce similar results, and the choice between the two techniques is largely based on individual preferences (UCLA Statistical Consulting Group, 2017; Stock & Watson, 2011).

Model Fit. Within the SEM framework there are several methods available to test for the model for goodness of fit. The research literature suggests that several different fit statistics should be employed to assess fit from different perspectives (Bollen & Long, 1993, Geiser, 2013). Each of the goodness of fit tests cited in the literature provide some index of the departure of the model structure from the observed data, which can aide the researcher in determining if model paths need to be added or deleted to improve the overall estimation of the model (Winship & Mare, 1983; Little, 2013). The indices selected for the current study include: 1) the likelihood ratio χ^2, 2) Comparative Fit Index (CFI), 3) the Tucker-Lewis Index (TLI), 4) the root mean square error of approximation (RMSEA), and 5) the standardized root mean square residual (SRMR).

The likelihood ratio χ^2 goodness of fit test is one of the most common measures of model fit (Keith, 2006; Kenny, 2014). The χ^2 goodness of fit tests the difference between the observed data and the hypothesized model (Norman & Streiner, 2003, Geiser, 2013). When testing for model fit, a smaller χ^2 value is desired because a smaller value indicates that the hypothesized model fits the data. For example, $\chi^2 = 0$ represents a perfect fit of the model-implied covariance matrix to the observed covariance matrix. It is important to note that χ^2 goodness of fit method is impacted by the sample size. Because the degrees of freedom for χ^2 goodness of fit tests equals the total number of parameters in the model minus the number of freely estimated parameters, models that rely on small sample sizes will have difficulty detecting differences between the model and the data because the standard errors will be large; and conversely models that have extremely large samples may be overly sensitive and detect minute differences that may not represent true model fit (Norman & Streiner, 2003; Little, 2013). Specifically, models that have more than 400 cases, the χ^2 statistic is almost always statistically significant (Kenny, 2014). Given that the proposed sample will include more than 3,000 cases, it is likely that the χ^2 in this study will be statistically significant, which could lead to a Type II error. To further assess model fit and reduce the probability of committing a Type II error, the CFI and TLI fit indices will be included.

Two incremental fit indices will be examined, CFI and TLI. Both the CFI and TLI compare the fit of the existing hypothesized model with that of a null, or independence model (Keith, 2006; Kenny, 2014; Little, 2013). The TLI is largely based on the χ^2 ratio, however this index adjusts for the model's degrees of freedom (Kenny, 2014). The RMSEA is designed as an approximation of the fit of a model, and yields an estimate of the average discrepancy per degree of freedom (Keith, 2006). Because statistical models are designed to approximate the population being studied, rather than provide a perfect fit, the RMSEA provides a more reasonable measure of model fit than the χ^2 (Keith, 2006). An additional advantage of the RMSEA index is the ability to calculate confidence intervals, which provides the researcher information about the precision in the estimate (Kenny, 2014; Geiser, 2013). The SRMR is an absolute measure of fit and is the standardized difference between the observed and predicted correlations (Kenny, 2014). The

SRMR is a positively biased measure, with a stronger bias for studies with a small sample sizes (Kenny, 2014).

General guidelines are available to assist researchers with interpretation of the CFI, TLI RMSEA, and SRMR indices; however there is no universally agreed upon standard for the χ^2 ratio (Kenny, 2014). Values approaching 1.00 for the CFI and TFI suggests a better fit, with values over .95 representing a good fit of the model to the data and .90 representing an adequate fit (Keith, 2006; Geiser, 2013; Little, 2013). For the RMSEA index values below .05 suggests a close fit of the model (Keith, 2006; Geiser, 2013; Little, 2013). More refined guidelines for RMSEA interpretation dictate that 0.01, 0.05, and 0.08 represent an excellent, good, and mediocre fit, respectively (MacCallum, Browne, & Sugaware, 1995). Finally, because the SRMR is an absolute measure of fit, a value of zero indicates perfect fit; therefore values closer to 0 indicate a better model fit (Kenny, 2014). Statistical significance was set to an alpha level of $< .05$. This alpha level was selected to adequately control the risk of making a Type I error, which is rejecting a null hypothesis that is actually true (Keith, 2006).

Chapter IV

Results

Three main research questions guided this study. Research Question 1 was designed to examine the temporal relationships among the key early warning system (EWS) variables: attendance, behavioral incidents, course grades, and standardized assessment performance. Research Questions 2 and 3 focused on the impact of the EWS variables on postsecondary outcomes. Research Question 2 specifically addressed the predictive validity of the key EWS variables on immediate postsecondary enrollment, and Research Question 3 examined the relationship between the key EWS variables and persistence in postsecondary education. Based on the findings documented in the literature review provided above, three hypotheses were developed to answer each of the research questions. This chapter reviews the descriptive statistics, construction of the cross-lagged panel model used to answer Research Question 1, and the use of that cross-lagged panel model to answer Questions 2 and 3.

Descriptive Statistics

Univariate descriptive statistics were calculated for each of the variables included in the model. Prior to conducting analyses all variables were checked for accuracy and normality. Minimum and maximum values for each variable were examined to determine if any values appeared to be out of range. One value appeared to possibly be a data entry error, where one student had a behavioral incident value of 121 during the 8th grade year, which had a corresponding *z*-score of 22.06 based on the mean and standard deviation for behavioral incidents for that year. This value appeared to be an extreme value and was an outlier in the dataset. The next highest value in the dataset for a behavioral incident was 59. The value of 121 was removed from the dataset, and excluded from data analysis.

The sample size, means, standard deviations, skewness, and kurtosis values are provided in Table 4 for each of the EWS variables used in the cross-lagged panel model. As Table 4 highlights, there were no concerns about normality for GPA and state assessment. However, there were issues with skewness and kurtosis for all of the attendance and behavioral incidents variables. To correct for the issues of skewness and kurtosis a reflected logarithmic transformation (Tabachnick & Fidell, 2007) was applied to each attendance variable. To correct for skewness and kurtosis for the behavioral incident variables a logarithmic transformation (Tabachnick & Fidell, 2007) was applied to each behavioral incident variable. The *adjusted skewness* and *adjusted kurtosis* columns in Table 4 provide the adjusted values. Appendix C provides a matrix of the correlations among all of the variables used in this study.

Table 4. *Univariate descriptive statistics for the predictor and outcome variables*.

Variable	N	Mean (*SD*)	Adjusted Mean (*SD*)	Skewness	Kurtosis	Adjusted Skewness	Adjusted Kurtosis
Predictor Variables							
Attendance							
7th	2179	.95 *(.07)*	.66 *(.33)*	-5.69	47.29	.17	.37
8th	2142	.92 *(.07)*	.83 *(.33)*	-3.38	21.02	.23	.17
9th	2347	.96 *(.07)*	.55 *(.36)*	-5.08	36.13	.50	.25
10th	2147	.96 *(.05)*	.53 *(.34)*	-5.24	48.31	.34	-.11
11th	2058	.94 *(.07)*	.68 *(.36)*	-3.60	19.06	.25	-.09
12th	2099	.93 *(.08)*	.78 *(.34)*	-3.31	15.06	.18	.15
Behavior							
7th	2179	1.70 *(4.69)*	.74 *(.34)*	6.07	51.85	-.74	-1.11
8th	2142	2.17 *(5.57)*	.71 *(.36)*	7.33	108.30	-.63	-1.32
9th	2347	1.36 *(3.94)*	.79 *(.33)*	6.70	75.99	-1.06	-.57
10th	2147	0.90 *(2.48)*	.83 *(.30)*	4.91	31.75	-1.32	.04
11th	2058	0.64 *(2.18)*	.87 *(.27)*	7.05	71.29	-1.72	1.36
12th	2099	0.58 *(1.97)*	.88 *(.26)*	5.97	47.68	-1.88	1.98
GPA							
7th	2134	3.16 *(.74)*	--	-.94	.28	--	--
8th	2102	3.13 *(.74)*	--	-.89	.26	--	--
9th	2269	2.80 *(.93)*	--	-.75	-.11	--	--
10th	2098	2.87 *(.82)*	--	-.75	.12	--	--
11th	2007	2.86 *(.79)*	--	-.67	-.05	--	--

Variable	N	Mean (*SD*)	Adjusted Mean (*SD*)	Skewness	Kurtosis	Adjusted Skewness	Adjusted Kurtosis
12th	2048	2.97 *(.80)*	--	-.88	.45	--	--
State Assessment							
MS State	2188	3.79 *(1.07)*	--	-.74	-.28	--	--
HS State	2173	3.65 *(.99)*	--	-.46	-.36	--	--
Outcome Variables							
	% Yes	% No					
Enrolled	65%	35%					
Persisted	47%	53%					

Missing Data

Prior to conducting preliminary and primary analyses an analysis of missing data was completed to determine the amount of missing data present in the current sample. Missing data was expected because the sample included students who both moved in and out of the district. On average, 23% of data was missing within each variable. Overall, 47% of cases had complete data on all variables. The covariance coverage across variables utilized in this study ranged from approximately 50-70% for the primary EWS variables in the analysis, but were 100% for the demographic variables used as covariates. Little's test for MCAR (Little, 1988) was statistically significant for the entire sample χ^2 (1703) = 6568.835, $p < .001$, suggesting that the data cannot be assumed to be MCAR. It is not possible to directly test for MAR (Enders, 2010); however, covariates were built in to the model to account for MAR and minimize the impact of the missing data. For example, a mobility covariate was included in the model, which provides information on both students who move in as well as students who move out of the partnering school district. Including this covariate in the model assumes that students who are mobile may be different from students who are not mobile, and thus helps account for missing data and adhere to the assumptions of MAR. The reason for missing data was not likely caused by the variables themselves (attendance, behavior incidents, GPA, or state assessment scores), which would be the case for MNAR. Preliminary and primary analyses were conducted using all data and data were assumed to be MAR.

Preliminary Analyses

The preliminary analyses were designed to address research Question 1, which included creating the cross-lagged panel model that would be used to subsequently address research Questions 2 and 3 centered on examining postsecondary outcomes. Mplus syntax from the preliminary analyses is presented in Appendix D. The preliminary analyses presented below are presented as a series of sequential model tests of several competing models.

Question 1: *What is the temporal relationship between the key EWS variables (i.e., attendance, behavior, course grades, and standardized assessment performance)?*

The first step in the preliminary analysis was to define the panel structure that would be used to estimate the model parameters for the primary analyses. To construct the basic multivariate cross-lagged panel model several steps were required. First, the autoregressive effects within each key EWS variable (i.e., attendance, behavioral incidents, GPA, and state assessment scores) were examined to determine the relationship among each set of predictor variables. The model was fitted to the data and the autoregressive paths were freely estimated. As demonstrated in Table 5, all autoregressive coefficients were statistically significant among each of the four key EWS variables. The autoregressive paths between GPAs had the largest effects. Overall, this model resulted in a "mediocre" or "poor" fit based on the fit indices used to evaluate the model. The RMSEA suggested a mediocre model fit with a value of 0.083 and the CFI suggested a poor fit with a value of 0.883. The results of this model suggest that additional paths should be added to improve the overall model fit.

In addition to the autoregressive paths, correlations among the residual variances of the key EWS variables within each academic year were also estimated. While the within-time residual correlations were not of specific interest to this study, they were included to help stabilize the cross-lagged panel model and ensure more reliable coefficient estimates from the primary analyses. The within-time correlations were also freely estimated. All within-time residual correlations were statistically significant at the $p < .01$ level, and ranged from small to large effect sizes. Effect sizes were defined as the following: small ≥ .10, medium ≥ .30, and large ≥ .50 (Fields, 2009; Keith, 2006). These effect sizes were chosen because they are widely accepted and used within educational research (Keith, 2006). Correlations among the residual variance for the key EWS variables within each academic year ranged from a small effect size of $r = .070$ (e.g., correlation between the residual variance for behavioral referrals in 11th grade and the residual variance for 11th grade attendance rate) to a large effect size of $r = .570$ (e.g., correlation between the residual variance for middle school state assessment and the residual variance of GPA in 7th grade). These results indicate that there is a small amount of shared variance within each year among the key EWS variables that can be explained above and beyond what can be explained by the autoregressive effects. These correlations are likely due to shared situation-specific effects that influence each of the key EWS variables at the same point in time.

Table 5. *Parameter estimates of the autoregressive paths*.

Autoregressive Path	β	*b*	SE	*p*
Attendance				
Att. 7 → Att. 8	.644	.632	.014	.000
Att. 8 → Att. 9	.589	.630	.015	.000
Att. 9 → Att. 10	.677	.675	.013	.000
Att. 10 → Att. 11	.677	.696	.013	.000
Att. 11 → Att. 12	.735	.708	.011	.000
Behavior				
Beh. 7 → Beh. 8	.561	.579	.015	.000
Beh. 8 → Beh. 9	.479	.433	.017	.000

Autoregressive Path	β	*b*	SE	*p*
Beh. 9 → Beh. 10	.564	.532	.016	.000
Beh. 10 → Beh. 11	.569	.514	.016	.000
Beh. 11 → Beh. 12	.558	.552	.016	.000
GPA				
GPA 7 → GPA 8	.840	.811	.007	.000
GPA 8 → GPA 9	.780	.902	.010	.000
GPA 9 → GPA 10	.848	.819	.007	.000
GPA 10 → GPA 11	.821	.793	.008	.000
GPA 11 → GPA 12	.788	.782	.009	.000
State Assessment				
MS State → HS State	.830	.767	.008	.000

Note: β = standardized regression coefficient; b = unstandardized coefficient; SE = standard error; *p* = significance level.

The second step in the preliminary analysis involved adding cross-lagged paths into the model. It was hypothesized that individual differences in GPA, attendance, and behavioral incidents would be influenced by temporally preceding behaviors and scores on the other variables. To test this hypothesis several cross-lagged paths were included in the model. It was hypothesized that previous GPA would negatively predict future behavioral incidents, previous GPA would positively predict future attendance, and previous attendance would positively predict future GPA. For each series of cross-lagged paths, the model was fitted to the data and the paths were freely estimated. Table 6 provides an overview of the results. All of the cross-lagged paths that estimated previous GPA's effect on future behavioral incidents were statistically significant. Compared to the simple panel structure described above in step one, including cross-lagged paths between GPA and future behavioral incidents significantly improved model fit ($\Delta\chi^2$ (5) = 857.20, $p < .001$). Similarly, all of the cross-lagged paths that estimated previous GPA's impact on future attendance were statistically significant. Again, including those additional cross-lagged paths significantly improved model fit ($\Delta\chi^2$ (5) 430.40, $p < .001$). The majority of cross-lagged paths that estimated previous year's attendance on future GPA were not statistically significant, with the exception of 7^{th} grade attendance's impact on 8^{th}

grade GPA. Adding this series of cross-lagged paths also significantly improved model fit ($\Delta\chi^2$ (5) =34.44, $p < .001$). Table 6 provides the parameter estimates for each of the cross-lagged paths that were included in the model.

Table 6. *Parameter estimates of the cross-lagged paths*.

Cross-Lagged Path	β	*b*	SE	*p*
1. Previous GPA effects on Future Behavior				
GPA 7 → Beh.8	.310	.146	.020	.000
GPA 8 → Beh. 9	.368	.156	.021	.000
GPA 9 → Beh. 10	.293	.101	.022	.000
GPA 10 → Beh. 11	.239	.076	.024	.000
GPA 11 → Beh. 12	.221	.068	.022	.000
2. Previous GPA effects on Future Attendance				
GPA 7 → Att.8	-.122	-.053	.019	.000
GPA 8 → Att. 9	-.270	-.127	.018	.000
GPA 9 → Att. 10	-.166	-.065	.020	.000
GPA 10 → Att. 11	-.146	-.059	.021	.000
GPA 11 → Att. 12	-.131	-.053	.020	.000
3. Previous Attendance effects on Future GPA				
Att. 7 → GPA 8	-.067	-.154	.013	.000
Att. 8 → GPA 9	-.016	-.044	.014	.256
Att. 9 → GPA 10	-.012	-.032	.013	.354
Att. 10 → GPA 11	-.020	-.049	.015	.169
Att. 11 → GPA 12	-.032	-.076	.016	.041

Note: β = standardized regression coefficient; b = unstandardized coefficient; SE = standard error; *p* = significance level.

The third and final step in the preliminary analysis included adding the covariates to the basic multivariate cross-lagged panel model. While covariates were not specific variables of interest within the cross-lagged panel model, they were included to account for their effects on the outcome measures. Each of the key EWS variables at the 7th grade time point were regressed on each of the covariates and covariates were allowed to correlate with each other. Table 7 provides an overview of the parameter estimates for the regression outcomes of the covariates impact on the key EWS indicators at 7th grade.

Table 7. *Parameter estimates of the impact of covariates on 7th grade EWS indicators*.

Covariate Path	β	*b*	SE	*p*
Covariate effects on Att. 7				
Gender	-.015	-.010	.020	.448
Race	.051	.014	.024	.037
Free/Reduced Lunch Status	.117	.083	.023	.000
Special Education Status	.068	.077	.019	.000
Gifted Status	-.055	-.074	.018	.003
English Language Learner	-.061	-.073	.024	.012
Mobile	.202	.141	.023	.000
Covariate effects on Beh. 7				
Gender	-.203	-.140	.017	.000
Race	.107	.028	.020	.000
Free/Reduced Lunch Status	-.276	-.159	.019	.000
Special Education Status	-.101	-.096	.017	.000
Gifted Status	.171	.069	.016	.004
English Language Learner	.035	.062	.020	.032
Mobile	-.165	.006	.020	.767
Covariate effects on GPA 7				
Gender	-.204	-.312	.019	.000
Race	.098	.069	.024	.000
Free/Reduced Lunch Status	-.221	-.442	.022	.000
Special Education Status	-.083	-.262	.019	.000
Gifted Status	.051	.516	.018	.000
English Language Learner	.052	.094	.024	.000
Mobile	.008	-.259	.027	.000
Covariate effects on MS State				
Gender	-.036	-.016	.016	.317
Race	-.366	-.153	.020	.000
Free/Reduced Lunch Status	-.427	-.184	.018	.000
Special Education Status	-.690	-.185	.015	.000
Gifted Status	.916	.210	.015	.000
English Language Learner	-.594	-.154	.019	.000
Mobile	-.512	-.225	.018	.000

Note: β = standardized regression coefficient; b = unstandardized coefficient; SE = standard error; *p* = significance level.

Table 8 provides an overview of the model comparisons for each of the competing models described above (e.g., autoregressive paths only vs. autoregressive paths and cross-lagged paths). A series of χ^2 difference tests were utilized to analyze the competing models and compare the results to determine if additional paths increased model fit. The competing models were nested models, which means that one model could be derived from the other by constraining or deleting paths (Keith, 2006). This table provides an overview of the construction of the basic multivariate cross-lagged panel model, which was used to answer Research Question 1. The results showed that there was a statistically significant temporal relationship among the key EWS variables. Hypothesis 1 was upheld. The results indicated that all autoregressive paths were statistically significant among the key EWS variables. These results suggested that previous behaviors within each of the EWS variables significantly predicted subsequent year's behaviors. In addition, the results of the nested model comparisons revealed that adding cross-lagged paths to the model resulted in statistically significant improvements in model fit. Specifically, these results suggested that previous GPAs had statistically significant impacts on future behavior incidents and attendance rates. The final multivariate cross-lagged panel model (Table 8, Model 6) was used as the base model for the primary analyses used to address the main research questions around postsecondary outcomes. The final cross-lagged panel model only contained statistically significant paths for the autoregressive, cross-lagged, and covariate paths that were previously included in the model. The standardized estimates for all paths in the final model are shown in Figure 2.

Table 8. *Results of the nested model comparisons for the cross-lagged panel model*.

Model	χ^2	*df*	$\Delta\chi2$	Δ*df*	CFI	TLI	RMSEA	SRMR
1. Autoregressive Paths	3224.79	148	--	--	.883	.853	.083	.238
2. Cross-lagged GPA→Beh. Added	2367.59	143	857.20*	5	.916	.892	.071	.173
3. Cross-lagged GPA→Att. Added	1937.19	138	430.40*	5	.932	.909	.065	.099
4. Cross-lagged Att. →GPA. Added	1902.75	133	34.44*	5	.933	.907	.066	.095
5. Covariates Added	2545.92	245	--	--	.925	.899	.055	.078

Model	χ^2	*df*	$\Delta\chi2$	Δ*df*	CFI	TLI	RMSEA	SRMR
6. Final Model	2569.06	254	20.14	9	.924	.902	.054	.079

Note: * $p < .001$; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; SRMR = Standardized Root Mean Square Residual.

In longitudinal research it is often thought that autoregressive and cross-lagged effects of variables are highly correlated and should be held constant (Little, 2013). To test this assumption all structural paths, including the autoregressive and cross-lagged paths among each key EWS variable (i.e., attendance, behavior, GPA, and state assessment) were constrained to be equal across time (Little, 2013). The constrained structural model was compared against the freely estimated structure model to determine if there was a statistically significant change in model fit. The results indicated that there was a statistically significant improvement in model fit when the paths among the EWS variables were freely estimated rather than constrained ($\Delta\chi^2$ (16) = 167.89, $p < .001$). The final cross-lagged panel model without equality constraints on autoregressive or cross-lagged paths was used to answer research Questions 2 and 3.

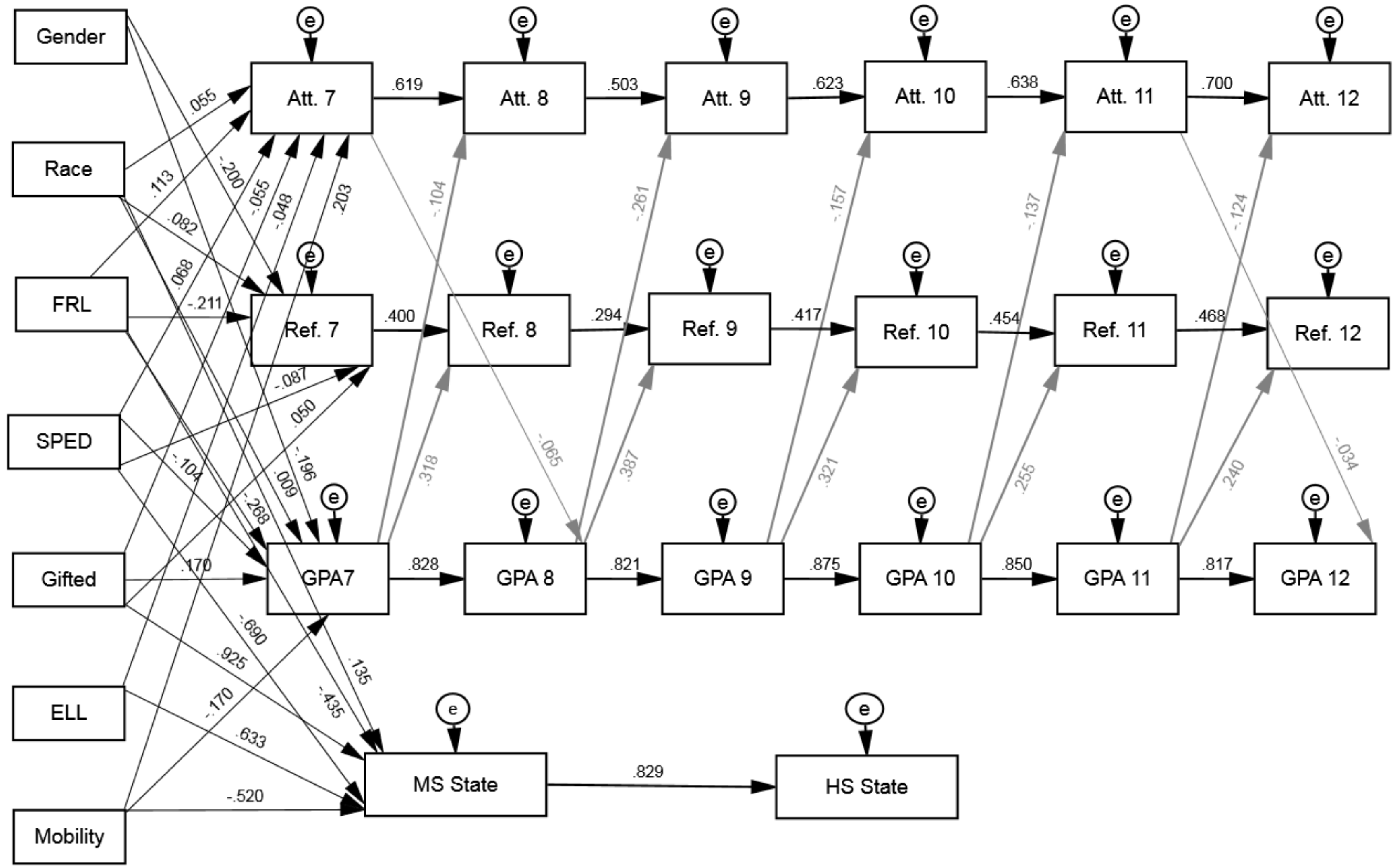

Figure 2. Structural model for the final cross-lagged panel model. All paths included in the final cross-lagged panel model were statistically significant at $p < .05$. Paths for the residual correlations are not present in the above model, but were estimated as part of the analyses.

Primary Analyses

The primary analyses were designed to answer the two main research questions focused on postsecondary outcomes. Question 2 examined the predictive validity of the EWS indicators on initial postsecondary enrollment. Question 3 investigated the predictive validity of the EWS indicators on postsecondary persistence. Mplus syntax from the primary analyses is presented in Appendix E (output for initial enrollment analyses) and Appendix F (output for persistence analyses). Separate analyses were completed for each research question.

Question 2: *Which key EWS variables are significantly related to postsecondary enrollment?*

A series of nested model comparisons were conducted to elucidate which EWS variables predict postsecondary enrollment. Seven primary models were examined to determine which EWS variables had statistically significant impacts on postsecondary enrollment and at what time point. Model 1 examined the impact of EWS variables at 12th grade and each subsequent model added data from the previous academic years (e.g., Model 2 examined 11th grade, Model 3 examined 10th grade, etc.). The final model (Model 7) estimated the impact of the covariates (e.g., gender, ethnicity, etc.) on postsecondary enrollment. The outcome variable used to address this research question was dichotomous (i.e., immediately enrolled in a postsecondary institution vs. did not immediately enroll), which required nonlinear regression techniques to estimate direct effects of the EWS indicators and covariates. A probit regression model with a robust weighted least squares estimator (WLSMV) was used to analyze the data.

Beginning with 12th grade, a series of models were estimated where predictors from each previous grade were entered into the model one grade level at a time. Each model was fitted to the data, and parameters were freely estimated. Regression parameters for each of the EWS variables estimated in the model were examined to determine the statistical impact. Variables that were not statistically significant were sequentially removed from the model. Results from the pruning process are presented in Table 10. This process was applied for each grade level included in this study (i.e., 11th – 7th grades). After the 7th grade EWS variables were added to the model and a final model was identified, modification indices for the final model were examined to ensure no variables were inadvertently removed and should be reintroduced into the model. The modification indices did not suggest that any of the variables removed from the models during the pruning process should be added back into the model.

Table 9 highlights the findings from the final model, including the direct, indirect, and total effects of each of the EWS variables and covariates on postsecondary enrollment immediately following high school graduation. It is important to remember that the coefficients produced by the probit regression models represent the change in the *z*-score (probit index) for one unit change in the predictor (UCLA Statistical Consulting Group, 2017). Further, the direct impact of the statistically significant variables must be considered and interpreted in combination with each other.

The results revealed that three EWS variables and three covariates had statistically significant direct effects on postsecondary enrollment (see Table 9). Hypothesis 2 was partially upheld. Hypothesis 2 speculated that 12th grade GPA, 12th grade attendance, 12th grade behavioral referrals, 9th grade GPA, and 7th grade GPA would significantly predict postsecondary enrollment. The results, however, indicated that 12th grade GPA, 12th grade attendance, and 7th grade GPA were the only statistically significant EWS predictors of postsecondary enrollment. Further, the results demonstrated that GPAs at 7th and 12th grades had the largest relative impact on postsecondary enrollment. Figure 3 highlights the standardized estimates for the EWS variables and covariates that produced statistically significant direct effects.

Table 9. *Standardized and unstandardized probit coefficients for direct, indirect, and total effects of the EWS variables and covariates on postsecondary enrollment*.

Variable	Direct Effect		Indirect Effect		Total Effect	
	β	*b*	β	*b*	β	*b*
Attendance						
12th Grade	-.091*	-.263*	.000	.000	-.091*	-.263*
11th Grade	.000	.000	-.071*	-.208*	-.071*	-.208*
10th Grade	.000	.000	-.059*	-.187*	-.059*	-.187*
9th Grade	.000	.000	-.051*	-.159*	-.051*	-.159*
8th Grade	.000	.000	-.035*	-.114*	-.035*	-.114*
7th Grade	.000	.000	-.014	-.043	-.014	-.043
Behavior						
12th Grade	.000	.000	.000	.000	.000	.000
11th Grade	.000	.000	.000	.000	.000	.000
10th Grade	.000	.000	.000	.000	.000	.000
9th Grade	.000	.000	.000	.000	.000	.000
8th Grade	.000	.000	.000	.000	.000	.000
7th Grade	.000	.000	.000	.000	.000	.000
GPA						
12th Grade	.219**	.275**	.000	.000	.219**	.275**
11th Grade	.000	.000	.194**	.254**	.194**	.254**
10th Grade	.000	.000	.175**	.221**	.175**	.221**
9th Grade	.000	.000	.159**	.177**	.159**	.177**
8th Grade	.000	.000	.166**	.235**	.166**	.235**
7th Grade	.338**	.477**	.167**	.235**	.504**	.712**
State Assessment						
High School	.000	.000	.000	.000	.000	.000
Middle School	.000	.000	.000	.000	.000	.000
Covariate						
Gender	.020	.040	.076*	.153*	.096**	.193**
Race	-.007	-.014	-.052**	-.113**	-.059	-.127
FRL Status	-.079*	-.164**	-.171**	-.358**	-.250**	-.522**
SPED Status	-.122**	-.410**	-.056**	-.188**	-.178**	-.598**
Gifted Status	.055	.216	.097**	.380**	.152**	.596**
ELL Status	-.029	-.101	.001	.005	-.027	-.096
Mobile	-.122**	-.251**	-.041**	-.083**	-.163**	-.334**

Note: * $p < .05$; ** $p < .001$.For this model, the threshold is equal to 1.564.

It is important to note that the relationship among each respective EWS variable and postsecondary enrollment was largely dependent on the entrance of other EWS variables from the preceding years. For example, each year that GPA was introduced into the model this variable demonstrated a statistically significant impact on postsecondary enrollment. However, when the preceding year's GPA was added in the next model, the previous year's GPA would either become non-statistically significant or negative, with the exception of 12th grade GPA that remained statistically significant throughout.

Table 10 provides an overview of the nested model comparisons for each of the competing models described above (e.g., 12th grade only vs. 11th grade added). This table offers a detailed description of the path removal process by identifying the specific instances that each of the statistically non-significant variables were removed from the model. Each model with a number only (e.g., Model 2) indicates the step where a previous grade level's EWS variables were included in the model. Each model with a number and letter (e.g., Model 2a) indicates when a non-statistically significant path was removed from the model. According to Muthén and Muthén (1998-2011), when using the WLSMV estimators the conventional approach to χ^2 difference testing (i.e., the difference between the χ^2 values for the two models and the difference between the degrees of freedom for the two models is checked for significance using the χ^2 table) is not appropriate because the χ^2 difference is not distributed as a χ^2 distribution. To adjust for the non-normality associated with the WLSMV estimator, the Mplus DIFFTEST command (Muthén & Muthén, 1998-2011) was applied to obtain corrected χ^2 difference testing output. When the DIFFTEST function is used both the χ^2 and the degrees of freedom (*df*) are calculated differently than the calculations applied in the traditional χ^2 difference testing approach (Bowen & Guo, 2011). To obtain the adjusted difference test, the DIFFTEST procedure required two steps. First, the less restrictive model (H1), the model with more free parameters, was estimated and the SAVEDATA command was used to save the derivatives of the H1 model for use in the second step of analysis (Muthén and Muthén, 998-2011). The second step required the more restrictive H0 model to be estimated and the nested model comparison command (DIFFTEST) was also included as part of the analysis.

The results of the nested model comparisons suggested that adding each preceding year of EWS data statistically significantly improved model fit. Removing the non-statistically significant direct paths did not impact the overall model fit. Additional fit indices were examined to evaluate the overall model fit. The additional fit indices also suggested an improvement in model fit when data from previous years was included in the model.

Table 10. *Results of the nested model comparisons for the initial enrollment models*.

Model	χ^2	*df*	$\Delta\chi2$	Δ*df*	CFI	TLI	RMSEA	WRMR
1. 12th Grade	1544.31	277	--	--	.932	.907	.039	1.379
2. 11th Grade	1544.31	277	34.67*	3	.932	.907	.039	1.379
2b. Ref. 12 removed	1523.95	275	1.14	1	.933	.908	.038	1.670
2c. Att 11 removed	1523.47	276	1.82	1	.933	.908	.038	1.367
2d. Ref 11 removed	1526.23	277	3.50	1	.933	.908	.038	1.369
3. 10th Grade	1526.23	277	31.06*	3	.934	.909	.038	1.355
3b. Att 10 removed	1501.02	275	1.00	1	.934	.909	.038	1.355
4. 9th Grade	1501.02	275	33.36*	3	.935	.910	.038	1.343
4b. Ref 9 removed	1479.56	273	1.99	1	.935	.910	.038	1.343
4c. Att 9 removed	1478.33	274	1.14	1	.935	.911	.038	1.344
5. 8th Grade	1478.33	274	30.21*	3	.937	.911	.038	1.331
5b. Ref 8 removed	1452.32	272	1.07	1	.937	.912	.038	1.331
5c. GPA 10 removed	1454.54	273	1.13	1	.936	.912	.037	1.331
5d. Att 8 removed	1452.04	274	.95	1	.937	.913	.037	1.331
5e. GPA 11 removed	1454.42	275	1.92	1	.937	.913	.037	1.332
5f. Ref 10 removed	1455.93	276	1.65	1	.937	.913	.037	1.332
6. 7th Grade	1455.93	276	32.00*	4	.938	.913	.037	1.319
6b. Ref7 removed	1430.60	273	1.00	1	.938	.914	.037	1.319
6c. Att 7 removed	1423.98	274	1.03	1	.938	.915	.037	1.319
6d. GPA 9 removed	1425.93	274	1.98	1	.938	.915	.037	1.319
7. Covariates	1425.93	275	--	--	.938	.915	.037	1.319

Note: * $p < .001$; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; WRMR = Weighted Root Mean Square Residual.

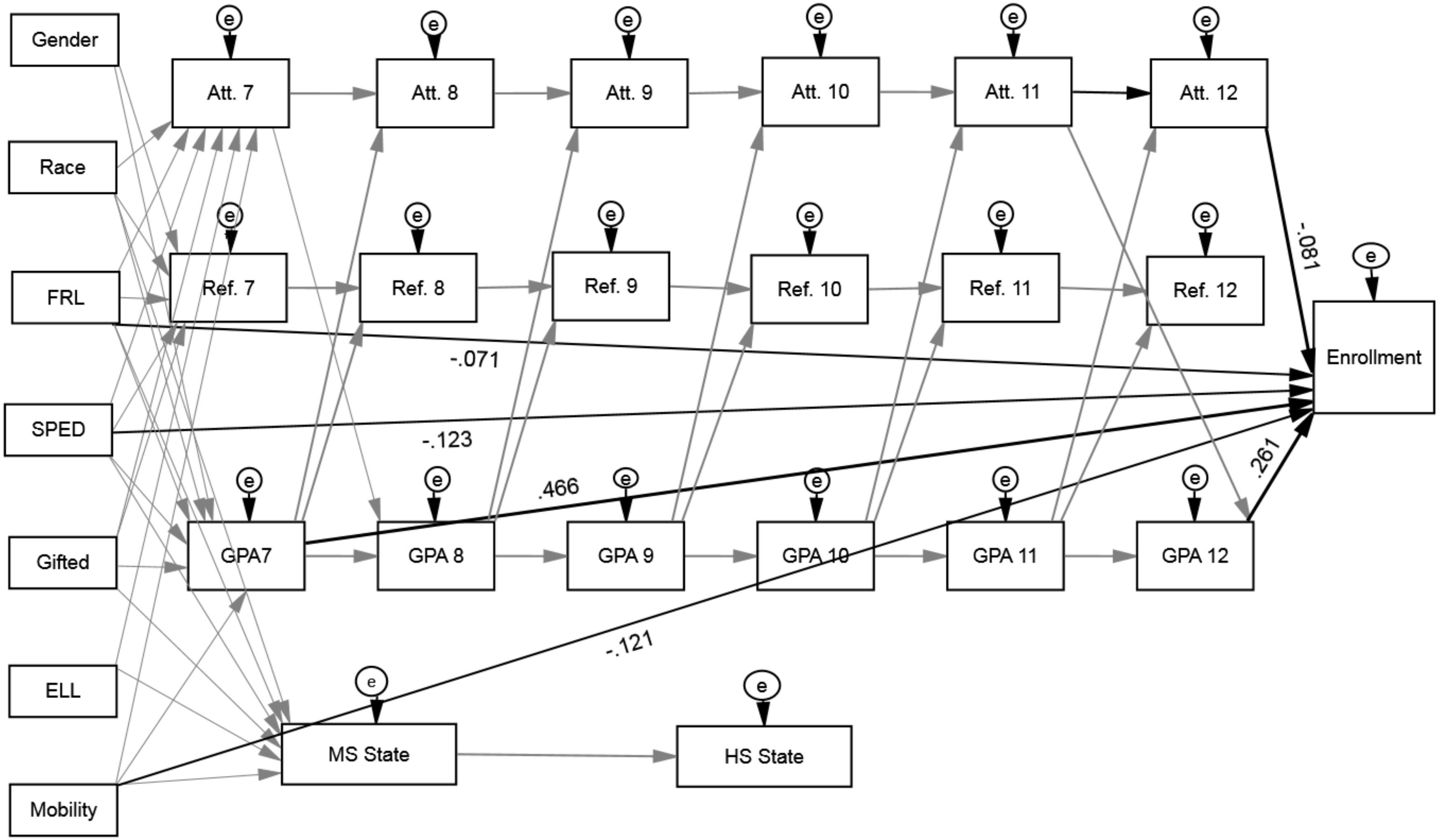

Figure 3. Structural model for the final enrollment model. The direct paths that are represented in this model include the statistically significant standardized estimates at the $p < .05$. Paths for the residual correlations are not present in the model for clarity, but were estimated as part of the analyses. Threshold = 1.564; $R^2 = .450$, $p < .001$.

Question 3: *Which key EWS variables are significantly related to postsecondary persistence?*

The methods that were applied to address research Question 3 were similar to those used to answer Question 2. To identify the EWS variables that had a statistically significant direct effect on postsecondary persistence a series of nested model comparisons were conducted. Seven primary models were examined to determine which EWS variables had statistically significant impacts on postsecondary persistence and at which time points. Model 1 examined the impact of EWS variables at 12th grade and Models 2-6 added data from the previous academic years (e.g., Model 2 examined 11th grade data, Model 3 examined 10th grade variables, etc.). Model 7 estimated the impact of the covariates (e.g., gender, ethnicity, etc.) on postsecondary persistence. The outcome variable used to address Question 3 was also a dichotomous variable (i.e., persisted in at least six semesters vs. did not persist), which required nonlinear regression techniques to estimate the direct effects of the EWS variables and covariates. A probit regression model with a robust WLSMV was used to analyze the data.

Beginning in 12th grade, a series of models were estimated where predictors from each pervious grade were entered into the model one grade level at a time. The series of models were designed to identify and estimate the impact of each of the EWS variables on postsecondary persistence across the target six years. The model was fitted to the data, and parameters were freely estimated. Regression parameters for each of the EWS variables estimated in the model were examined to determine the statistical impact. For each of the six models, a pruning process was applied where variables that were not statistically significant were sequentially removed from the model one at a time. Because the autoregressive paths among each set of EWS variables were highly correlated, multicollinearity issues impacted the regression estimates produced by the path analyses for the persistence models. To address this issue the standardized estimates produced by each model were checked for accuracy. Estimates that were out of plausible ranges or unrealistic were removed from the model (e.g., $\beta > +/- 1.00$). Results from the pruning process, including the removal of unrealistic, negative estimates are presented in Table 13. This process was applied for each grade level included in this study (i.e., 11^{th} – 7^{th} grades).

Table 11 highlights the findings from the final model, including the direct, indirect, and total effects of each of the EWS variables and covariates on postsecondary persistence in at least six semesters. Again, the regression coefficients produced by the probit regression models and present in Table 11 are representative of the impact of the EWS variables on the changes in the *z*-score in predicting the outcome. Further, the direct impact of the statistically significant variables must be considered and interpreted as a combination of linear effects. The results of Model 7, which included all of the statistically significant EWS variables across the target six years as well as the covariates, revealed that two EWS variables (i.e., GPA 11 and middle school state assessment) and three covariates (i.e., special education status, mobility, and free/reduced lunch status) had a statistically significant impact on postsecondary enrollment. Modification indices were checked to determine if any statistically significant paths were inadvertently removed from the model during the pruning process. The modification indices corresponding to Model 7's output suggested that 7^{th} and 8^{th} grade GPA may be statistically significant predictors and should be reintroduced to the model.

To adhere to this modification suggestion, GPA 7 and GPA 8 were added back into the final model and were freely estimated. The results revealed that when GPA 7, GPA 8, and middle school assessment were all included in the model none of the target variables were statistically significant (GPA 7, $\beta = .353$, $p = .075$; GPA 8, $\beta = -.102$, $p = .637$; MS State = .043, $p = .445$). Further, when only one GPA variable (7^{th} or 8^{th} grade GPA) was included along with middle school assessment, the GPA indicator was statistically significant and the middle school state assessment variable became non-significant. For example, when both GPA 7 and middle school state assessment were estimated in the model, GPA 7 was statistically significant and middle school state assessment was not (GPA 7, $\beta = .261$, $p < .001$; MS State = -.049, $p = .350$). Similarly, when both GPA 8 and middle school state assessment were estimated in the model together, GPA 8 was statistically significant and middle school state assessment was not (GPA 8, $\beta = .266$, $p < .001$; MS State = -.053, $p = .336$). Finally, when only one target variable was included in the model that respective variable was statistically significant. To determine which middle school academic measure should remain in the final model the AIC and BIC were compared for each competing model. The first follow-up model examined the fit index when GPA 7 was freely estimated (AIC = 50490.96; BIC = 51462.12) and GPA 8 and middle school state assessment were removed from the model. The second follow-up model examined the fit index when GPA 8 was freely estimated (AIC = 50533.43; BIC = 51504.59) and GPA 7 and middle school state assessment were removed from the model. Finally, the third follow-up model freely estimated the impact of middle school state assessment performance (AIC = 50555.40; BIC = 51526.56) and GPA 7 and GPA 8 were removed from the model. The results indicated that freely estimating GPA 7 and removing the other two variables from the model produced the better fitting model.

To further test whether GPA 7 should be included in the model, nested model comparisons were conducted. The follow-up nested model comparisons examined the differences in fit between the competing models. Model 7 was used as the baseline model for the follow-up nested comparisons, where middle school state assessment was freely estimated. A nested model comparison was conducted which examined the impact of reintroducing GPA 7 back into the model. The results of the nested model comparisons revealed that adding GPA 7 back into the final model resulted in a statistically significant improvement in model fit ($\Delta\chi^2$ (1) = 18.04, p = .000). The final follow-up nested model comparison examined the impact of removing the middle school state assessment path. The results to this follow-up test indicated that removing middle school state assessment from the model did not result in statistically significant change in model fit ($\Delta\chi^2$ (1) = 1.896, p = .169). These results further support and corroborate the findings of the AIC and BIC model comparisons that suggested leaving GPA 7 in the model and removing middle school state assessment.

Hypothesis 3 speculated that 12th grade GPA, 12th grade attendance, 12th grade behavioral referrals, 9th grade GPA, and 7th grade GPA would significantly predict the probability that a student would persistence in postsecondary education. Hypothesis 3 was partially upheld, as 7th grade GPA was a statistically significant predictor of postsecondary persistence. However, the hypothesis was not upheld for 12th grade GPA, 12th grade behavioral referrals, and 9th grade GPA. Figure 4 highlights the standardized estimates for the EWS variables and covariates that produced statistically significant direct effects in the final persistence model.

Table 11. *Standardized and unstandardized probit coefficients for direct, indirect, and total effects of the EWS variables and covariates on postsecondary persistence*.

Variable	Direct Effect		Indirect Effect		Total Effect	
	β	*b*	β	*b*	β	*b*
Attendance						
12th Grade	.000	.000	.000	.000	.000	.000
11th Grade	.000	.000	.000	.000	.000	.000
10th Grade	.000	.000	.000	.000	.000	.000
9th Grade	.000	.000	.000	.000	.000	.000
8th Grade	.000	.000	.000	.000	.000	.000
7th Grade	.000	.000	.027*	.081*	.027*	.081*
Behavior						
12th Grade	.000	.000	.000	.000	.000	.000
11th Grade	.000	.000	.000	.000	.000	.000

Variable	Direct Effect		Indirect Effect		Total Effect	
	β	*b*	β	*b*	β	*b*
10^{th} Grade	.000	.000	.000	.000	.000	.000
9^{th} Grade	.000	.000	.000	.000	.000	.000
8^{th} Grade	.000	.000	.000	.000	.000	.000
7^{th} Grade	.000	.000	.000	.000	.000	.000
GPA						
12^{th} Grade	.000	.000	.000	.000	.000	.000
11^{th} Grade	.435**	.571**	.000	.000	.435*	.571**
10^{th} Grade	.000	.000	.394**	.497**	.394**	.497**
9^{th} Grade	.000	.000	.360**	.401**	.360**	.401**
8^{th} Grade	.000	.000	.342**	.484**	.342**	.484**
7^{th} Grade	.227**	.320**	.342**	.482**	.569**	.802**
State Assessment						
High School	.000	.000	.000	.000	.000	.000
Middle School	.000	.000	.000	.000	.000	.000
Covariate						
Gender	.007	.013	.108**	.204**	.115**	.217**
Race	-.021	-.046	-.062**	-.134**	-.083*	-.180*
FRL Status	-.054*	-.112*	-.184**	-.385**	-.238**	-.498**
SPED Status	-.125**	-.419**	-.062**	-.208**	-.187**	-.628**
Gifted Status	.045	.178	.107**	.421**	.152**	.599**
ELL Status	-.038	-.134	-.002*	-.009*	-.041	-.142
Mobile	-.133**	-.274**	-.040**	-.082**	-.173**	-.356**

Note: * $p < .05$; ** $p < .001$. The threshold for this model is equal to 2.539.

Similar to the results seen in the postsecondary enrollment models, the relationship among each respective EWS variable for the postsecondary persistence models was largely dependent on the entrance of other EWS variables from the preceding years. Unlike the enrollment models, multicollinearity concerns were an issue for the persistence models. As described above, several variables had to be removed from the model because of unrealistic parameter estimates.

Table 12 provides an overview of the nested model comparisons for each of the competing models described above (e.g., 12^{th} grade only vs. 11^{th} grade added). Additionally, Table 12 includes a detailed description of the pruning process that was applied to remove the statistically non-significant variables. This table highlights the specific instance within the construction of the final path model that each variable was identified as non-significant. Each model with a number only (e.g., Model 2) indicates a step where a previous grade level's EWS variables were included in the model. Each model with a number and a letter (e.g., Model 2a) indicates that a non-statistically significant path was removed from the model. Similar to the procedures described for the enrollment model comparisons, the Mplus DIFFTEST (Muthén & Muthén, 1998-2011) was utilized to obtain corrected χ^2 values and degrees of freedom. The differences between the competing nested models were examined.

The results of the nested model comparisons suggested that adding each preceding year of EWS data significantly improved model fit. Removing the non-significant direct paths did not impact the overall model fit. Additional fit indices were examined to evaluate the overall model fit. The additional fit indices also suggested an improvement in model fit when data from previous years was included in the model.

Table 12. *Results of the nested model comparisons for the persistence models*.

Model	χ^2	*df*	$\Delta\chi2$	Δdf	CFI	TLI	RMSEA	WRMR
1. 12th Grade	1553.01	277	--	--	.932	.908	.039	1.378
1b. Att 12 removed	1536.32	278	1.044	1	.933	.909	.038	1.379
2. 11th Grade	1553.01	277	49.424**	2	.932	.908	.039	1.379
2b. Ref. 11 removed	1532.02	276	.322	1	.933	.909	.038	1.367
2c. Att 11 removed	1513.75	277	1.620	1	.934	.910	.038	1.368
2d. GPA12 removed	1515.34	278	1.802	1	.934	.911	.038	1.368
2e. Ref removed	1518.02	279	3.653	1	.934	.911	.038	1.360
3. 10th Grade	1518.02	279	8.835*	3	.934	.911	.038	1.369
3b. Att 10 removed	1511.30	277	1.246	1	.934	.911	.038	1.362
3c. GPA 10 removed	1512.66	278	12.820**[1]	1	.934	.911	.038	1.366
4. 9th Grade	1512.66	278	5.938	3	.934	.911	.038	1.366
4b. Ref 9 removed	1528.69	276	1.007	1	.933	.909	.038	1.362
4c. Att 9 removed	1506.10	277	.110	1	.935	.911	.038	1.363
4d. Ref 10 removed	1507.34	278	2.705	1	.935	.911	.038	1.363
5. 8th Grade	1507.34	278	30.540**	3	.935	.911	.038	1.363
5b. Att 8 removed	1496.07	276	1.281	1	.935	.912	.038	1.356
5c. GPA 9 removed	1496.07	277	58.908**[1]	1	.935	.912	.038	1.356
6. 7th Grade	1496.07	277	48.205**	4	.935	.912	.038	1.356
6b. Ref 8 removed	1449.04	274	.214	1	.938	.914	.038	1.323

Model	χ^2	*df*	$\Delta\chi2$	Δ*df*	CFI	TLI	RMSEA	WRMR
6c. Att 7 removed	1439.17	275	.664	1	.938	.915	.037	1.234
6d. GPA 8 removed	1451.45	276	25.832**[1]	1	.938	.914	.037	1.332
6e. GPA 7 removed	1451.84	277	1.240	1	.938	.915	.037	1.332
6f. HS State removed	1485.13	279	57.548**[1]	1	.936	.913	.037	1.354
7. Covariates	1446.12	272	--	--	.938	.913	.037	1.332
8. Final Model	1428.02	272	--	--	.939	.915	.037	1.314

Note: ** $p < .001$; *$p < .05$; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root Mean Square Error of Approximation; WRMR = Weighted Root Mean Square Residual. [1]Although these variables were removed from the model and resulted in a statistically significant change in fit, they were removed because they produced impossible standardized coefficients (β > +/- 1.00).

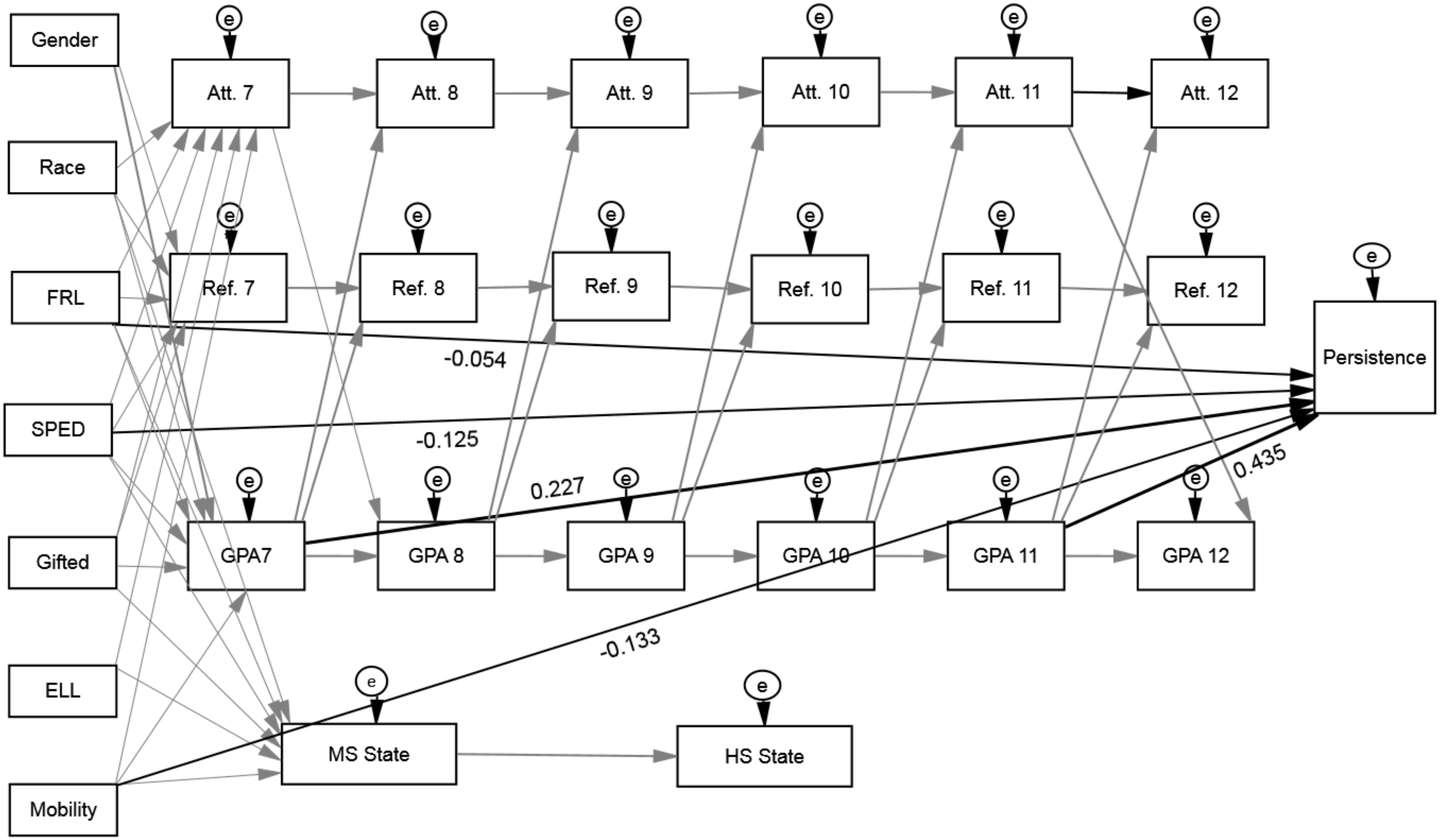

Figure 4. Structural model for the final persistence model. The direct paths that are represented in this model include statistically significant standardized estimates at the $p < .05$. Paths for the residual correlations are not present in the above model, but were estimated as part of the analyses. Threshold = 2.539; $R^2 = .542$, $p < .001$.

Chapter V

Discussion

The purpose of this study was to determine the predictive validity of key early warning system (EWS) variables, commonly used in dropout prevention systems, on postsecondary outcomes. A large body of research has examined and validated the utility of the key EWS variables on predicting dropout behavior in high school (e.g., Allensworth & Easton, 2007; Bafanz et al., 2007; Davis et al., 2013; Dynarski, et al., 2008; Heppen & Therriault, 2008; Jerald, 2006a). However, very little empirical evidence exists that utilizes the EWS framework as a means to study the predictive validity of key early warning indicators on postsecondary success, and the majority of this work has been limited in scope (e.g., only utilizing EWS variables from one or two time points, only examining postsecondary enrollment as an outcome measure). Although this study was primarily an exploratory analysis, the results provide an overview of the longitudinal impact of the key EWS variables on postsecondary enrollment and persistence.

This chapter summarizes the results and offers an interpretation of the main findings of this study. The results of the analyses are explored in terms of the context of the larger research literature on college readiness. The implications for practice, limitations of the current study, and future research directions are discussed.

Summary of Findings

Preliminary Analyses. The purpose of the preliminary analyses was to address research Question 1 which sought to explore the temporal relationship among the key EWS variables. Additionally, the preliminary analyses were designed to create the basic multivariate cross-lagged panel model that was utilized to answer the primary research questions centered on postsecondary success.

Hypothesis 1. It was predicted that there would be a significant temporal relationship among each of the key EWS variables. As predicted, Hypothesis 1 was confirmed. The results indicated that all autoregressive paths among each set of EWS variables (i.e., attendance, behavior, GPA, and state assessment scores) were statistically significant between temporally preceding academic years. This finding indicates that previous year's performance and behavior significantly predicted future year's performance and behavior.

In addition to examining the statistical impact of each variable, effect sizes were also analyzed to determine the magnitude of effects. Examining effect size was an important component of interpreting the results of this study because several variables were identified as being statistically significant; however, their magnitude of effects were too small to be considered meaningful influences on student performance and behavior (Keith, 2006). The autoregressive effects among each EWS indicator were considered to be a large magnitude of effect. The rule of thumb that was applied to this study to judge the magnitude of effect was small $\geq .10$, medium $\geq .30$, and large $\geq .50$ (Fields, 2009; Keith, 2006).

The magnitude of effects among the GPA variables had the largest effects among all of the EWS variables (β ranged from .780 to .840). Each year students tended to earn a GPA similar to the GPA they earned in the previous year. For example, students who earned a high GPA in the previous year were more likely to earn a high GPA the following year. The magnitude of effects among middle school and high school state assessments ($\beta = .830$) was similar to GPA. Relative to the other EWS variables, it appears that the academic indicators had the largest temporal effects on subsequent performance. Although the magnitudes of effects were not as large for the attendance and behavior EWS variables, these variables still demonstrated a statistically significant temporal effect. The magnitude of effects for attendance was also considered a large effect size (β ranged from .589 to .735). The magnitude of effects for behavior ranged from a moderate to large effect size (β ranged from .479 to .569).

When first identifying the panel model only the autoregressive effects were estimated, and there were some concerns with overall model fit. Cross-lagged paths and covariates were also included in the model and estimated. Including the cross-lagged paths into the panel model significantly improved model fit. This step was important as it helped stabilize the basic multivariate model that was later used for the primary analyses.

The majority of the cross-lagged paths produced statistically significant impacts on subsequent year's variables; however, not all estimates indicated a meaningful effect. The cross-lagged paths that estimated the impact of previous year's GPA on future year's behavioral incidents had the largest magnitude of effects (β ranged from .221 to 368). This finding suggests that student's academic performance in the previous year had an impact on their behavior in the subsequent years. Specifically, students who had higher GPAs the previous year had fewer behavioral referrals/incidents the following year. The cross-lagged paths between GPA and attendance were also statistically significant, but the magnitude of effects was considered to be small (β ranged from -.131 to -.270). These findings suggest that student's previous GPA had a small impact on their succeeding year's attendance rates. Specifically, students who had higher GPAs tended to have higher attendance rates (recall that the attendance variables had to be transformed to adjust for skewness and kurtosis concerns, and through this process this variable was reflected, which is why these estimates are negative).

Primary Analyses. The purpose of the primary analyses was to address research Questions 2 and 3, both of which were centered on postsecondary success. Specially, research Question 2 was designed to identify the EWS variables that were predictive of postsecondary enrollment, and at which time point. Research Question 3 was designed to identify the EWS variables that were predictive of postsecondary persistence.

Prior to beginning a discussion about the results that address research Questions 2 and 3, a small caveat is necessary. Throughout interpretation of the outcome models and their respective findings it is important to remember that the models were estimated using probit regression techniques. As such, the impact of the statistically significant EWS indicators is modeled as a linear combination of all statistically significant indicators (Long, 1997; Muthén, 1998-2004; Nagler, 1994; UCLA Statistical Consulting Group, 2017). Further, the probit regression coefficients provided below represent the change in the *z*-score (or probit index) for one unit change in the predictor (UCLA Statistical Consulting Group, 2017). Therefore, the probability associated with each outcome variable (i.e., enrollment and persistence) will depend on the changes across the total combinations of statistically significant predictor variables within that model.

Hypothesis 2. It was predicted that 12th grade GPA, 12th grade attendance, 12th grade behavioral referrals, 9th grade GPA, and 7th grade GPA would predict the probability that students would enroll in a postsecondary institution the fall semester immediately following high school graduation. Hypothesis 2 was partially upheld. The results revealed that 12th grade GPA, 12th grade attendance, and 7th grade GPA were the only EWS variables that had a statistically significant direct impact on predicting the probability of postsecondary enrollment. The academic indicators of 12th and 7th grade GPA both had a relatively large impact on the probability that a student would enroll ($\beta = .219$, $b = .275$ and $\beta = .338$, $b = .477$, respectively). These findings represented a meaningful impact on the prediction, with 7th grade GPA demonstrating the largest effect on the change in the conditional probability *z*-score. These findings suggest that students who had higher GPAs in 7th and 12th grades were more likely to enroll in a postsecondary institution the fall semester immediately following high school graduation. The third EWS variable that was deemed statistically significant was 12th grade attendance (β = - .091, b = -.263). While this variable had a statistically significant direct impact on predicting the outcome, the relative magnitude of effect on the conditional probability z-score was small. Students who had higher attendance rates in 12th grade were statistically more likely to enroll in a postsecondary institution compared to students who had lower attendance rates.

In addition to the three key EWS indicators that had a statistically significant direct effect on predicting postsecondary enrollment, three covariates also had statistically significant direct effects on postsecondary enrollment. Free and reduced lunch status, special education status, and mobility variables all directly impacted the conditional probability of enrolling in postsecondary education, but each covariate had a relatively small direct effect (β = -.079, b = -.164; β = -.122, b = -.410; and β = -.122, b = -.251, respectively) on the change in z-score. Students who received free and reduced priced lunches, received special education services, or changed schools at least one time during 7th-12th grades were less likely to enroll in a postsecondary institution immediately following high school graduation. The impact of the covariates on postsecondary enrollment was largely mediated through other variables included in the model, and six of the seven covariates had statistically significant indirect effects on postsecondary enrollment (i.e., Gender, Race, FRL, SPED, gifted, and mobility). This means the impact of covariates directly impacted the outcome of the EWS variables earlier in the model, and as a result very little variance from the covariates remained to account for difference in predicting postsecondary enrollment. For example, the impact of free and reduced lunch status had a moderate-sized direct effect on student's 7th grade GPAs. Students who received free and reduce lunches tended to have a lower 7^{th} grade GPA than students who did not receive free and reduced lunches. Because GPA across the years was highly correlated, these students tended to continue to have a lower GPA throughout their middle and high school academic careers, and the impact of free and reduced lunch status was mediated through each of these variables. As a result, this subgroup of students was less likely to enroll in college in the fall semester after graduation. Of the covariates that indirectly impacted the probability of enrolling in a postsecondary institution, free and reduced lunch status had the largest relative effect ($\beta = -.171$, $b = -.358$).

Taken together, the findings from this study indicate that students who had a higher GPA in 7^{th} and 12^{th} grades, had a higher attendance rate in 12^{th} grade, did not receive special education services, did not receive free or reduced priced lunches, and did not transfer schools during 7^{th} – 12^{th} grades were more likely to enroll in college the fall semester immediately following high school graduation. The following examples highlight how the changes in the probit coefficients reported above for the statistically significant predictors impact students' probability of enrolling. For example, if student 1 had a 12^{th} grade GPA of 4.00, 7^{th} grade GPA of 4.00, above average attendance rate (represented as a reflected log transformation of 0.50), did not receive special education services, did not receive free and reduced priced lunches, and did not transfer schools during the target years, he/she would have a 91% probability of enrolling in college right after high school. Student 2, on the other hand, had a similar profile, however, this student did receive special education services. Because special education status decreased a student's probability of enrolling, student 2 would have an 81% probability of enrolling. Finally, student 3 had a 12^{th} grade GPA of 3.00, a 7^{th} grade GPA of 3.50, above average attendance, did not receive special education services, did not receive free and reduced priced lunches, and did not transfer schools during the target six years, he/she would have a 79% probability of enrolling in college directly after high school. Student 3 had the lowest 12th and 7th grade GPAs, and because GPA had the largest relative impact on the change in *z*-score used to predict enrollment status, student 3 had the lowest probability of enrolling.

Hypothesis 3. It was predicted that 12th grade GPA, 12th grade attendance, 12th grade behavioral referrals, 9th grade GPA, and 7th grade GPA would predict the probability that students would persist at a postsecondary institution for at least six semesters or secure a postsecondary degree or credential, whichever came first. Hypothesis 3 was partially upheld. The results revealed that 11th grade GPA and 7th grade GPA were the only EWS indicators that had a statistically significant direct effect on the conditional probability that a student would persist in postsecondary education for at least six semesters ($\beta = .435$, $b = .571$ and $\beta = .227$, $b = .320$, respectively). The primary predictors of persistence in a postsecondary setting were largely academic and related to how a person did in their classes as measured by their GPA. Both 7th and 11th grade GPAs had relatively large direct effects on the probability that a student persisted; 11th grade GPA had the largest impact on the change in *z*-score used to calculate the predicted probability. These findings suggest that students who had higher GPAs in 7th and 11th grades were more likely to be continuously enrolled in a postsecondary institution for at least six semesters. It is important to note that while GPAs from the other respective grade levels did not have a statistically significant direct effect on the probability that a student would persist, each of these variables had a statistically significant indirect effect on the outcome, with the exception of 12th grade GPA. Further, the total effect of 7th grade GPA (direct and indirect effects combined) had the largest impact on predicting postsecondary persistence ($\beta = .569$, $b = .809$).

Similar to the postsecondary enrollment model summarized above, the same three covariates that had statistically significant direct effects on the probability that a student would initially enroll in college also demonstrated statistically significant direct effects on the probability that a student would persist in college. Free and reduced lunch status, special education status, and mobility were all directly related to the probability that a student would persist in postsecondary education. Each covariate had a relatively small direct effect on the change in *z*-score used to calculate the conditional probability of the outcome. Students who received free and reduced priced lunches, received special education services, and/or changed schools at least one time during 7th-12th grades were less likely to continuously enroll in and persist in postsecondary education.

Again, the impact of the covariates on postsecondary persistence was largely mediated through other EWS indicators present in the model. Similar to the results described above for postsecondary enrollment, the majority of the variance explained by the covariates was accounted for through their direct effect on the 7th grade EWS variables, and as a result very little variance remained to account for differences in the probability that a student would persist. Of the covariates that indirectly affected postsecondary persistence, free and reduced lunch status had the largest relative impact on the probability of persisting (β = -.184, *b* = -.385). These results suggest students who receive free and reduced priced lunches were more likely to have lower GPAs in 7th grade and these results were mediated through each grade level, thus impacting student's subsequent GPAs and future postsecondary persistence.

In sum, the findings from this study indicate that students who had a higher GPA in 7th and 11th grades, did not receive special education services, did not receive free or reduced priced lunches, and did not transfer schools during 7th-12th grades were more likely to persist in at least six semesters in postsecondary education or secure a 2-year degree or credential, whichever occurred first. Similar to the example provided above for the enrollment model, the following example demonstrates the differential impact of the probit coefficients on the prediction model for persistence. If student 1 had an 11^{th} grade GPA of 4.00, 7^{th} grade GPA of 4.00, above average attendance rate (represented as a reflected log transformation of 0.50), did not receive special education services, did not receive free and reduced priced lunches, and did not transfer schools during the target years, he/she would have an 85% likelihood of persisting in college. If student 2 had a similar profile, but did move at least once during the target years, this student's probability of persisting in college drops to 77%. Finally, student 3 had a lower academic profile than the previous two students. Student 3 had an 11^{th} grade GPA of 3.00, a 7^{th} grade GPA of 2.50, did not receive special education services, did not receive free and reduced priced lunches, and did not move during the target years. Because the academic indicators had the largest relative impact on the conditional probability for persistence, student 3 had the lowest probability of persisting at 50%.

General Discussion

When the results of the present study are compared to prior research on the EWS framework and college readiness literature an interesting picture of the impact of the EWS indicators on postsecondary outcomes unfolds. The present study's findings that academic indicators are the strongest predictors of postsecondary success are consistent with prior research on both EWSs (e.g., Dynarski & Gleason, 2002; Johnson & Semmelroth, 2010; Wood, Kiperman, Esch, Leroux, & Truscott, 2017) and college readiness (e.g., ACT, 2015; Becker et al., 2014; MacIver & Messel, 2013). The following section provides a comprehensive examination of the present study's findings in juxtaposition to the EWS and college readiness literatures. This section highlights the consistencies and differences between the current findings and the larger literature.

The Impact of the EWS Variables. The majority of the early work on the EWS data management tool centered on risk factors present at 9th grade. This body of work found substantial support for the predictive validity of the EWS indicators at 9th grade in predicting future dropout behavior (e.g., Allensworth & Easton, 2005; Carl et al., 2013; Cohen & Smerdon, 2009; Curran Neild, 2009; Roderick, 2006). For example, Allensworth and Easton (2007) found that students who earned a 2.00 GPA or higher at the end of their freshman year were more likely to graduate from high school on-time (i.e., within 4 years) compared to their peers who earned a GPA of 1.99 or lower.

In a similar vein, the college readiness literature also highlights the importance of the 9th grade year as a predictor of college success. Becker and colleagues (2014) reported 9th grade GPA as a statistically significant predictor of postsecondary enrollment immediately following high school graduation. Consistent with the dropout literature that identified GPAs greater than 2.00 as the threshold for decreasing student's susceptibility to dropping out of high school (Allensworth & Easton, 2007), the college readiness literature has also identified 9th grade GPAs of 2.00 or greater as an indicator of postsecondary enrollment immediately following high school graduation (Durham et al., 2015). Based on this robust body of previous research it was hypothesized that 9th grade would also play a key role in predicting postsecondary outcomes (i.e., enrollment and persistence). The present study did not find the same support for the role of the 9th grade indicators in predicting postsecondary outcomes, although achievement was an important predictor of college enrollment and persistence.

Although support was not found for the 9th grade GPA indicator in the present study, there were several other areas in which the GPA indicator converged with previous literature. First, 12th grade GPA was predictive of postsecondary enrollment and 11th grade GPA was predictive of postsecondary persistence. High school GPA has been cited as the strongest predictor of the probability of enrolling and persisting in postsecondary education compared to other college readiness indicators, such as ACT scores and SES (Geiser & Santelices, 2007; Lotkowski et al., 2004). In both the enrollment and persistence models, late high school GPA was a statistically significant predictor of postsecondary success. Interestingly, there were minor variations in the respective grade level that GPA emerged as a predictive indicator (e.g., 12th grade vs. 11th grade) in the two models. Perhaps these differences exist between the two models because of differences in course enrollment and rigor between the two grade levels. It is possible that students enroll in more rigorous courses their 11th grade year, and opt to have a "lighter" and less rigorous course load their senior year. Greater success during a more rigorous academic year may be a better predictor of persistence in college, but greater success during one's last year in high school may be a better predictor of immediately enrolling in college. Data for course selection during 11th and 12th grades was not available for this study to test this hypothesis, but future research should explore the differential experiences between 11th and 12th grade to help inform the differences found in this study.

Second, grade data from early middle school had the strongest total effects on the probability of both enrolling and persisting in postsecondary education. These findings are consistent with previous research that highlights the importance of middle school. Before exploring the findings specific to middle school, it is important to recognize and note that the previously mentioned studies that highlighted 9th grade as important year in predicting dropout did not include data from earlier academic years. The following studies demonstrate that including middle school data can impact the overall interpretation of the EWS model and variables. Balfanz and colleagues (2007) and researchers from the Baltimore Education Research

Consortium (2011) both found that course failures in 6^{th} grade were highly predictive of future dropout behavior. While the previously mentioned studies highlighted 6^{th} grade as a critical grade level in which risk factors were present, Bowers (2010) found that statistically significant dropout indicators did not emerge until 7^{th} grade in a longitudinal study. Regardless of the specific year in which risk factors emerge, these studies taken together support the notion that middle school is a pivotal time for dropout prevention initiatives. The findings from the present study extend this notion, and suggest that middle school is also a prime opportunity for school districts to provide college readiness initiatives and interventions.

There were minor differences in the role of the attendance EWS indicator in predicting postsecondary outcomes, and generally this variable played a very minor role in predicting postsecondary outcomes. While there was a statistically significant direct effect for the 12^{th} grade attendance variable on predicting the probability that a student would enroll in postsecondary education, this effect was relatively small. Similarly, while there were statistically significant indirect effects for attendance's role in the enrollment model, these effects were also small. In the persistence model, attendance did not have any direct effects on the probability that a student would persist in higher education, and only had a small indirect effect on persistence at 7^{th} grade. These results were surprising given the relevance of the attendance indicator within the dropout EWS literature (e.g., Allensworth & Easton, 2005, 2007; Carl et al., 2013; Jerald, 2006a). Furthermore, the college readiness literature also highlights the importance of attendance rates in predicting college success. Becker and colleagues (2014) found attendance data was a statistically significant predictor of postsecondary enrollment.

Interestingly, the present study did not find support for the inclusion of the behavioral incidents indicator for an EWS inclusive of postsecondary outcomes. Previous research on the

EWS variables impact on dropout has identified behavior as a key predictor (e.g., Curran Neild & Balfanz, 2006; Heppen & Therriault, 2008). For example, Balfanz and colleagues (2007) found that students who had one or more out-of-school suspensions were more likely to dropout. Further, consequences to behavioral incidents, such as suspension policies, may act as a mechanism for pushing students out of school and inadvertently encouraging dropout behavior (Doll, Eslami, & Walters, 2013; Rotermund, 2007). While there was empirical support for the behavioral indicator within the dropout literature, none of the college readiness studies reviewed as part of the literature review for this study included a behavioral indicator as a potential predictor variable of postsecondary success. Based on this information it was reasonable to suspect that behavioral incidents would serve the same function as observed in the dropout literature and deter students from pursuing higher education. However, for both the enrollment and persistence models, behavior incidents did not have any effect (direct or indirect) on the outcome. Given the mixed literature on the reliability and validity of behavioral referrals (cf. Spaulding et al., 2010; Predy et al., 2014), it is possible the collection of this data may not have been as systematic as necessary (e.g., different schools within the district may have used differing standards on what constitutes a behavioral referral), and as a result may have limited the impact of this variable. Future research would need to further explore the data collection techniques used to gather this data to rule this out as a potentially confounding influence.

The Impact of the Covariates. Previous research has found disparities among racial and economically diverse groups with regard to college enrollment. Specifically, research has found that Black and Hispanic students are less likely than White students to immediately enroll in college following high school graduation (Greene & Foster, 2003). The impact of race did not have a statistically significant direct effect on postsecondary outcomes; however, for both the enrollment and persistence models race had an indirect effect on postsecondary outcomes. This finding suggests that the impact of race on postsecondary outcomes is largely mediated through the EWS indicators. Race had the largest impact on middle school state assessment performance, where non-White students were more likely to have lower state assessment scores compared to White students (β = -.366, *b* = -.153). Similarly, research has found that low-income students are also less likely to enroll and persist in college compared to students from middle to high-income households (Roderick et al., 2007). There was a statistically significant direct and indirect effect for SES, as measured by FRL status, on the probability that students would enroll and persist in higher education in the present study. Similar to previous research (e.g., Roderick et al., 2007), results revealed that students who were from lower income households were less likely to attend and persist in college. The results from the present study suggested that FRL status had the largest total effect on postsecondary success compared to the other covariates included in the model. The total effect of SES had a relatively moderate impact on predicting the probability in both the enrollment and persistence models (β = -.250, *b* = -.522; β = -238, *b* = -.498, respectively).

In addition to the impact of SES on postsecondary outcomes, the present study found support for the impact of mobility on postsecondary success. These findings are supported by previous research that have also identified mobility as a statistically significant predictor of dropout (Herbers, Reynolds, & Chen, 2013; Ou & Reynolds, 2008). Rumberger and Larson (1998) found that even one school transfer between 8th and 12th grades were correlated with a dropout rate that was twice as high as compared to students who did not transfer schools during that time period. Further, several studies have found that mobility predicts negative academic outcomes (e.g., dropout) above and beyond the effects of SES (Herbers et al., 2013; Lee &

Burkham, 2002; Rumberger & Larson, 1998). Finally, mobility during elementary and secondary school has been linked to postsecondary outcomes as well. Herbers and colleagues (2013) found that school moves between 4th and 8th grades were statistically significant predictors of the highest grade level completed. Herbers and colleagues (2013) study indicated that, on average, students who experienced two or more school moves completed approximately one quarter of year less education compared to students who did not move schools.

Finally, the results from the present study revealed a statistically significant impact of special education status on both postsecondary enrollment and persistence. These results are consistent with findings from both the dropout and postsecondary access literatures. Research has found that disability status has been linked to dropping out of high school (Hoff, Olson, & Peterson, 2015). For example, Synder and Dillow (2012) found approximately 22% of students with a disability left high school prior to graduating. Similar trends are seen within the college access literature as well. While postsecondary enrollment rates among students with disabilities have significantly increased, this population of students tends to have lower postsecondary retention rates (Herrington & Fogg, 2009). In a national investigation of postsecondary attainment among students with disabilities, on average, students with disabilities tended to delay enrollment in a postsecondary institution; whereas students without disabilities did not delay enrollment, and tended to enroll in a postsecondary institution the fall semester immediately following high school graduation (Newman et al., 2011). The present findings revealed a similar trend. Students who were identified and served by special education programs were less likely to immediately enroll and persist in postsecondary education. Although the impact of receiving special education services on predicting the probability of postsecondary outcomes was statistically significant, the effect size was relatively small ($\beta = -.122$, $b = -.410$; $\beta = -.125$, $b = -.419$ respectively).

Study Contributions. The findings from this study extend and contribute to the literature in several ways. First, the development and validation of the EWS framework has largely occurred within an urban context (e.g., New York, Chicago, Baltimore). This study extends this body of research by utilizing a sample from a moderately sized-school district located in the Midwest. The present study also enhances the scope of the EWS framework by exploring the temporal relationship among the key EWS variables. To the author's knowledge no previous EWS research has explored the structural relationship among the indicator variables used within an EWS framework. The present study sheds light on these relationships, and provides empirical evidence that highlights the autoregressive impact of each key EWS variable (i.e., attendance, behavior, GPA, and state assessment scores). Further, the findings from this study indicate that a relationship exists across several key EWS indicators. Specifically, the findings revealed the influence of cross-lagged paths between GPA, attendance, and behavioral incidents.

Furthermore, the present study extends the previous EWS literature by examining postsecondary success as an outcome. Very few studies have investigated the impact of the EWS indicators on postsecondary outcomes, and of the studies that have examined postsecondary outcomes, the primary focus has largely been centered on a snapshot in time, such as 9th grade (Becker et al., 2014; Soland, 2013). Previous research suggests that longitudinal research methodologies produce a more robust understanding of academic trajectories (Carl et al., 2013; Connolly et al., 2015; Bowers et al. 2013; Johnson & Semmelroth, 2010); however, very limited empirical evidence exists that examines the impact of postsecondary predictors within a longitudinal framework (Conley, 2007; Hein, Smerdon, & Sambolt, 2013). By examining the impact of EWS indicators on postsecondary outcomes using a longitudinal approach to data analyses, the present study captures a comprehensive overview of student's academic trajectories as they move through each grade level.

The findings from this study can be used to enhance the EWS framework and extend its application to include data-driven guidance on students' college readiness as they progress through each grade level. For instance, this study demonstrated that academic indicators (i.e., GPA) are statistically significant predictors of college success, and schools could use this information to drive intervention planning. The results from this study revealed that early middle school (i.e., 7th grade GPA) and late high school academic achievement (i.e., 11th and 12th grade GPA) were critical time points in predicting college readiness. As such, schools could strategically align supplemental tutoring and academic support services throughout these grade levels to encourage higher levels of achievement among all students.

Implications for Practice

In light of the findings from this study, several conclusions relevant to education policy around data use within schools can be extrapolated. School districts currently utilize EWSs as organizational data tools designed to help identify students who are at-risk of dropping out of high school (Allensworth, 2013). These EWS rely on and incorporate educational data that is easily collected by teachers and administrators. Data from the EWS is used to match students who are at-risk to the appropriate supports and interventions to prevent dropout. Findings from this study suggest that academic data that is currently utilized by the dropout EWS is also predictive of postsecondary outcomes. Based on these results, districts could easily incorporate a flag for college readiness into their current dropout EWS system, thus creating a dual-purpose data tool. Specific attention would be given to student's GPA as a gauge of college preparedness, as this indicator was the most predictive of future college success.

Within that same vein, school districts would be encouraged to use the EWS tool as a vehicle for communication in which they can engage staff in regular data-driven discussions around college readiness. These discussions are especially needed within the middle school years. The findings from the current study revealed that 7th grade GPA was a key predictor of college success. This academic indicator was the only EWS variable that was statistically significant in both the enrollment and persistence models. While later high school GPA (i.e., 11th and 12th grades) was also identified as an important predictor in both models, intervening this late in a student's secondary career leaves little time for remediation and targeted interventions. Beginning the discussion early in middle school may help alter the academic trajectory for some students, as long as appropriate interventions and supports are put in place.

To further support the uptake of the college readiness EWS flag, school districts are encouraged to devote resources to enhancing their overall college-going culture within their school buildings. A college-going culture builds the expectation that postsecondary education is an avenue all students can access (College Board, 2006). As the results of the present study indicate, academic achievement is one of the strongest predictors of college success. Given this information, schools that build a college-going culture would increase the academic rigor and demands outlined within their curriculum, as well as offer additional academic supports for students who need supplemental services. A school-wide, college-going culture that creates access to rigorous curriculum helps ensure all students have the opportunity to develop a solid academic record, which will strengthen their ability to enroll and persist in college (Knight-Manuel, 2016; McKillip, Godfrey, & Rawls, 2012). In addition to offering rigorous curriculum, schools that create a college-going culture also provide students opportunities to engage in "college talk" and provide necessary information and recourses on postsecondary education (Knight-Manuel, 2016).

Finally, three covariates emerged as statistically significant predictors in both models (i.e., special education status, free and reduced lunch status, and mobility). While there is little that school districts can do to change these variables, districts can indirectly influence the impact of these variables. For example, districts can offer additional supports and interventions to this subgroup of students as a means of mitigating the negative impacts associated with these variables. In this study, all three of these covariates were identified as risk factors, and decreased a student's likelihood of enrolling and persisting in college. As such, the specific strategies and interventions that districts would be encouraged to adopt should be designed to foster student's resilience. Furthermore, the findings from this study suggest interventions should begin as early as possible. These initiatives could include additional academic supports (e.g., tutoring services) or counseling and mentoring strategies to increase student's self-efficacy for college readiness during middle and high school. During late high school counselors and staff could work with at-risk populations to connect them to resources located on the college campus they will be attending. Connecting students to college resources during high school helps to facilitate a smooth transition (Castleman & Paige, 2013), as well as hopefully increase the likelihood that they will persist in postsecondary education.

Limitations

There are several limitations to this study that need to be considered when interpreting the results. It is important to note that this study was primarily designed to investigate the impact of the specific early warning indicators used within the EWS framework (i.e., attendance, grades, behavior, and standard assessment scores). As such, the additional variables that have been identified within the research literature as predictors of postsecondary success were not included in the model because they did not fit within the EWS framework. However, because this study did not include data on these variables (e.g., ACT/SAT, course enrollment histories), results should be interpreted with caution as other external variables may have influenced postsecondary success among the study's sample.

First, the sample that was utilized in this study was fairly homogenous. The majority of the participants in this study were White students from a relatively affluent school district. It is possible that different results would have been obtained with a more diverse sample of participants. Previous research indicates that there are disparities among racial and economically diverse groups with regard to college enrollment and persistence (e.g., Bryant, 2015; Roderick et al., 2011). It is possible that there are differences in the relative importance of the EWS indicators in predicting postsecondary success among varying subgroups of student populations. Additionally, this study only examined data from one school district located within the Midwestern United States. Due to the limited scope of the sample there are limitations to the study's external validity that warrant caution when generalizing findings to the larger student population.

Next, there were multiple unaccounted for variables in the present study that may have influenced the stability of the panel structure or the ultimate impact on the postsecondary outcomes. Previous research has identified several academic indicators as important predictors of postsecondary success that were not included in the present study. For example, colleges and universities frequently utilize ACT and/or SAT scores for admissions purposes, as research has identified these variables as predictive of postsecondary success (e.g., Conley, 2008; Kless et al., 2013; ACT, 2015; Becker et al., 2014; Cromwell et al., 2013). These variables were not available for this study, and were not included in analyses. Again, it is possible that including these variables in the model would have impacted the relative influence of the other EWS indicators.

Another set of unaccounted for variables include specific course enrollment. Previous research has identified course selection as an important predictor of success in college. For example, students who complete a rigorous core curriculum (i.e., four years of English, three years of mathematics, three years of science, and three years of social studies) and Advanced Placement courses are more likely to go to college than students who do not elect to take these courses (Cromwell, 2013; Leonard, 2011; Zhao & Liu, 2011). More specifically, mathematics course enrollment has been identified as a highly predictive indicator of postsecondary success. Studies have found that students who enroll in a mathematics class equivalent to Algebra II or higher are more likely to attend college than students who do not take these more advanced mathematics courses (Adelman, 2006; Bowers et al., 2013; Byun et al., 2015). Furthermore, Trigonometry or higher has been identified as the tipping point for postsecondary degree attainment (Adelman, 2006). It is possible that including course enrollment as a potential predictor within an EWS framework would have implications for the relative impact of GPA on postsecondary success. For example, students who enroll in a more rigorous course load may actually have lower GPAs because of the difficulty of these courses. This raises an important question, when students enroll in more rigorous and potentially more difficult courses does this alter the relative impact of GPA as a predictive indicator of college success? Therefore, it is likely that including both course enrollment information and GPA into an EWS framework would provide a more nuanced picture of student achievement, and as a result a more refined EWS data management tool.

Additionally, previous research has identified college knowledge as a key predictor of future college success (Borsato et al., 2013; Gurantz & Borsato, 2012). College knowledge includes the necessary skills and understanding that enable a student to successfully access and navigate the postsecondary context (Borsato et al., 2013). An example of college knowledge includes an understanding of the financial requirements for college (e.g., cost of tuition, financial aid options). While this set of knowledge and skills is likely to influence a student's enrollment and persistence in higher education, this data is not readily available from school districts. As such, it is often not included as an EWS indicator and was not included in this study.

Grade retention (e.g., not promoting a student to the next grade level) has also been identified as a significant risk factor that is predictive of a plethora of negative outcomes, including dropout (e.g., Alexander et al., 2001; Jimerson et al., 2002; Roderick et al., 2009). While this variable would likely impact postsecondary outcomes, the present study did not include this variable in the model. The variable was not included because inclusion of this variable in the model would make data analyses overwhelmingly complex because students could have repeated grades at different time points and this would have required multiple years of outcome data. However, this is a variable that should be investigated more thoroughly in future research.

Further, this study did not include any data from the elementary school years. A robust body of research literature highlights that risk factors leading to eventual dropout can be traced back to early elementary school (e.g., Alexander et al., 2011, Bradshaw, O'Brennan, & McNeely, 2008; Janosz, Archambault, Morizot, & Pagani, 2008). Given this understanding within the dropout context, it could be speculated that similar early schooling factors would influence postsecondary success as well. Unfortunately, this study could not directly explore and test this speculation, as elementary data was not included in the model. However, the trend seen within the results of this study suggested that EWS variables within earlier years impacted and influenced postsecondary outcomes. For example, the results demonstrated that the impact of each respective EWS variable was largely dependent on the entrance of the other EWS indicators from the preceding years. Based on these results it is hypothesized that including EWS variables from elementary school would produce similar patterns, though this would need to be specifically tested.

Free and Reduced Lunch (FRL) status was incorporated into this study as a proxy measure of socioeconomic status (SES). It is important to acknowledge and understand the limitations of this variable when it is applied and used as a proxy measure of SES. For example, the FRL variable only includes one aspect of SES, economic status, and does not consider other components of SES, such as parent/guardian occupation or education level (National Forum on Education Statistics, 2015). As such, the interpretation of this variable as it relates to SES should be largely centered on economic status. However, even within this interpretation caution is warranted. Recent policy changes, including the Community Eligibility Provision within the Healthy, Hunger-Free Kids Act has amended the eligibility criteria for FRL within high-poverty areas (National Forum on Education Statistics, 2015). Under this amendment, all students who attend school in a high-poverty area would qualify for free or reduced priced lunches. While the partnering district was not specifically situated within a high-poverty area, this limitation will be an important consideration in future research.

Finally, the model used in this study was very complex. The purpose of this study was to examine the impact of the key EWS variables on postsecondary outcomes through a longitudinal lens. While this investigative approach has several strengths associated with it, it also introduces a lot of complexity that can impact and complicate interpretation and application. As each academic year's worth of EWS data was introduced into the model this increased the number of variables that were added to the model. With each additional variable added to the model, the possible combinations and interactions increase geometrically, which can complicate the interpretation of which EWS indicators are most predictive of postsecondary success. As seen in the results, adding each preceding year's data into the model directly impacted the magnitude and relationships among the other variables within the model. However, the results indicated a model that made conceptual sense and was consistent with previous research. In general, the final models for predicting postsecondary enrollment and persistence were relatively simple when considering the enormously complex models that could have been identified.

Future Research

The results of the present study elicit a number of potential issues and questions that future research could address. The finding that early middle school and late high school GPAs were the most predictive indicators of college success raises an important question: How will school districts use this information to inform practice? Teachers already tend to know a great deal about their students, including their behaviors, attitudes, aspirations, and their academic performance within the classroom (Soland, 2015). As a result, teachers can have a direct influence over shaping student outcomes, and providing targeted interventions and supports. Because teachers already have a lot of the information EWS provide, future research should explore and validate the incremental utility of the EWS tool as it relates to college readiness. Specifically, it will be important to evaluate the value-added of an EWS tool intended to enhance and improve school's college planning efforts and supports. Specifically, does this tool add information and utility to the teacher's knowledge about their student's postsecondary potential above and beyond the knowledge they already possess just by nature of their daily interactions with students?

Another key issue that should be further explored in future research is the differential impact of course enrollment patterns and the potential impact these choices may have on overall GPA. As previously mentioned, research has found that course selection and enrollment patterns are related to postsecondary outcomes, including enrollment and persistence. Empirical evidence suggests that students who complete a rigorous core curriculum, including Advanced Placement courses are more likely to enroll in college than peers who do not elect to take these types of courses (Cromwell, 2013; Leonard, 2011; Zhao & Liu, 2011). While this finding makes sense within the larger college readiness literature, it is unclear how this evidence fits within an EWS framework. Future research should attempt to uncover the interaction between course enrollment, GPA, and postsecondary outcomes. Investigating this issue will help shape and inform school counseling practices. For example, would students be better served, in terms of postsecondary preparation, by enrolling in an easier course load to secure a potentially higher GPA or should students enroll in more rigorous courses and potentially jeopardize their overall GPA?

There are many choices a student has when it comes to postsecondary options. There are several different types of colleges students can choose to attend (e.g., 4-year liberal arts college; 2-year community college; 4-year highly selective university, etc.). The present study did not differentiate between the various types of higher education institutions, but rather examined postsecondary success through a broad lens. Given the wide array of postsecondary choices that exists, future research should compare the differential impact of the EWS indicators across the various institutional types. It is possible that the sets of EWS indicators that were identified as predictive of postsecondary success in this study would vary depending on the type of postsecondary institution examined as the outcome.

Finally, the present study utilized data from only one school district. While this study provides local validity evidence for the EWS indicators within the partnering school district, future research should incorporate data from multiple school districts across a wider scope of geographic locations. Including multiple school districts would allow for a comparison of the impact of the EWS indicators across contexts. This empirical comparison is essential to increasing the generalizability and application of the EWS indicators in predicting postsecondary success.

Finally, future research should include a qualitative component as part of the investigation of the EWS tool's utility in predicting postsecondary success. Future research should craft questions and studies that examine the conditions around the uptake and application of the EWS tool by educational practitioners. More specifically, this type of data would provide a deeper understanding about how the indicators are being used by educational practitioners. Qualitative data could also provide key insight into the impact of the overall school climate on facilitating and inhibiting the use of this tool.

Conclusion

The results from the present study extend the application of the EWS framework to include postsecondary success as an outcome measure of interest. The results are grounded in and supported by previous research that has identified core indictors of college readiness and success (e.g., ACT 2015, Becker et al., 2014; Belfield & Crosta, 2012; Kless et al., 2013) that overlap with EWS indicators that are currently used to flag students at-risk of dropout (e.g., Allensworth, 2013; Balfanz et al., 2007; Carl et al., 2013). Given these findings, school districts are encouraged to embed a postsecondary flag into their current EWS as a means to facilitating data-driven conversations around college readiness.

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Appendix A

Research Design

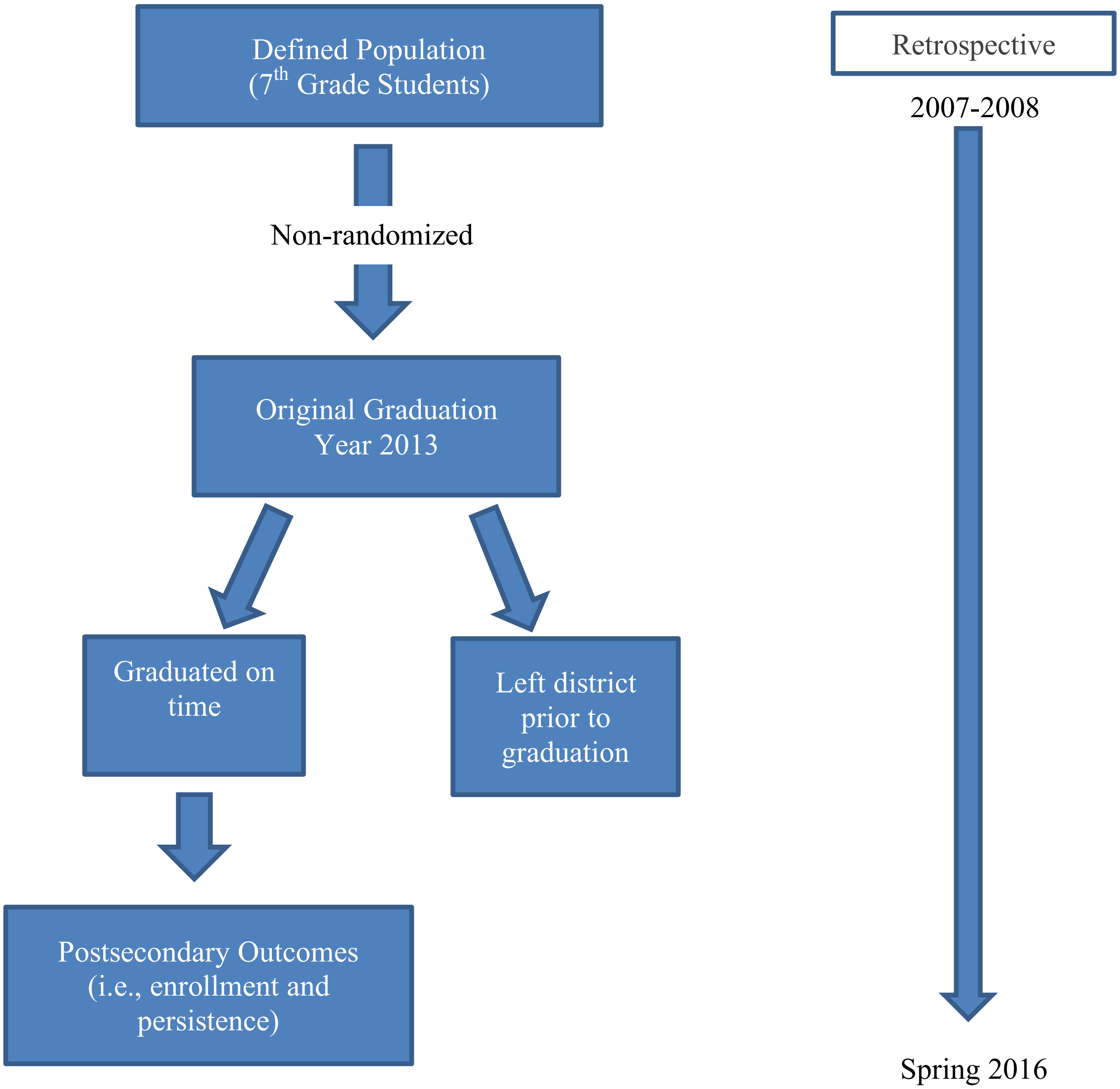

Figure 1. Overview of the study's design.

Appendix B

IRB Apporval

Meghan Ecker-Lyster
meecker@ku.edu

Dear Meghan Ecker-Lyster:
On 8/27/2015, the IRB reviewed the following submission:

Type of Review:	Initial Study
Title of Study:	Evaluating the Efficacy of an Early Warning System in Predicting Graduation and Postsecondary Outcomes: A Path Analysis
Investigator:	Meghan Lyster
IRB ID:	STUDY00003034
Funding:	None
Grant ID:	None
Documents Reviewed:	• Correspondence_for_STUDY00003034.doc, • HSCL_Initial_Submission_Form_EWS Dissertation.pdf,

The IRB approved the submission from 8/27/2015 to 8/26/2016.
Before 8/26/2016 submit a Continuing Review request and required attachments to request continuing approval or closure.
Any significant change to the protocol requires a modification approval prior to altering the project.
Notify HSCL about any new investigators not named in original application. Note that new investigators must take the online tutorial at https://rgs.drupal.ku.edu/human_subjects_compliance_training.
Any injury to a subject because of the research procedure must be reported immediately.
When signed consent documents are required, the primary investigator must retain the signed consent documents for at least three years past completion of the research activity.

If continuing review approval is not granted before the expiration date of 8/26/2016 approval of this protocol expires on that date.

Please note university data security and handling requirements for your project:
https://documents.ku.edu/policies/IT/DataClassificationandHandlingProceduresGuide.htm

You must use the final, watermarked version of the consent form, available under the "Documents" tab in eCompliance.

Sincerely,
Stephanie Dyson Elms, MPA
IRB Administrator, KU Lawrence Campus

Appendix C

Correlation Matrix

	Att7lg	Att8lg	Att9lg	Att10lg	Att11lg	Att12lg	Ref7lg	Ref8lg	Ref9lg	Ref10lg	Ref11lg	Ref12lg
Att7lg	1.000											
Att8lg	.623**	1.000										
Att9lg	.520**	.576**	1.000									
Att10lg	.461**	.521**	.620**	1.000								
Att11lg	.448**	.521**	.522**	.640**	1.000							
Att12lg	.418**	.461**	.454**	.565**	.714**	1.000						
Ref7lg	-.191**	-.195**	-.258**	-.225**	-.192**	-.220**	1.000					
Ref8lg	-.202**	-.241**	-.305**	-.270**	-.168**	-.209**	.568**	1.000				
Ref9lg	-.202**	-.252**	-.327**	-.313**	-.244**	-.276**	.446**	.507**	1.000			
Ref10lg	-.126**	-.178**	-.271**	-.358**	-.257**	-.257**	.386**	.432**	.556**	1.000		
Ref11lg	-.107**	-.152**	-.235**	-.272**	-.273**	-.265**	.359**	.344**	.456**	.542**	1.000	
Ref12lg	-.098**	-.134**	-.201**	-.230**	-.240**	-.280**	.261**	.291**	.399**	.463**	.549**	1.000
MsState	-.203**	-.200**	-.304**	-.215**	-.174**	-.148**	.347**	.350**	.422**	.333**	.274**	.236**
HsState	-.097**	-.149**	-.226**	-.242**	-.225**	-.181**	.253**	.283**	.334**	.362**	.282**	.246**
GPA7	-.397**	-.319**	-.415**	-.311**	-.260**	-.269**	.523**	.516**	.508**	.451**	.392**	.347**
GPA8	-.364**	-.422**	-.451**	-.348**	-.303**	-.324**	.490**	.566**	.549**	.466**	.383**	.349**
GPA9	-.297**	-.348**	-.509**	-.365**	-.301**	-.288**	.421**	.482**	.580**	.492**	.409**	.382**
GPA10	-.212**	-.257**	-.347**	-.433**	-.349**	-.318**	.352**	.387**	.466**	.532**	.446**	.392**
GPA11	-.235**	-.242**	-.317**	-.327**	-.444**	-.382**	.349**	.351**	.418**	.440**	.449**	.412**
GPA12	-.188**	-.204**	-.290**	-.297**	-.335**	-.441**	.332**	.312**	.396**	.418**	.439**	.444**
Enroll	-.172**	-.159**	-.211**	-.210**	-.207**	-.254**	.248**	.241**	.285**	.282**	.273**	.257**
Persist	-.164**	-.135**	-.223**	-.205**	-.233**	-.235**	.229**	.213**	.294**	.287**	.270**	.263**

	MsState	HsState	GPA7	GPA8	GPA9	GPA10	GPA11	GPA12	Enroll	Persist
Att7lg										
Att8lg										
Att9lg										
Att10lg										
Att11lg										
Att12lg										
Ref7lg										
Ref8lg										
Ref9lg										
Ref10lg										
Ref11lg										
Ref12lg										
MsState	1.000									
HsState	.805**	1.000								
GPA7	.638**	.532**	1.000							
GPA8	.602**	.521**	.837**	1.000						
GPA9	.619**	.613**	.774**	.813**	1.000					
GPA10	.563**	.621**	.698**	.727**	.833**	1.000				
GPA11	.543**	.565**	.693**	.687**	.733**	.807**	1.000			
GPA12	.518**	.503**	.627**	.641**	.662**	.702**	.783**	1.000		
Enroll	.363**	.326**	.454**	.434**	.391**	.395**	.422**	.453**	1.000	
Persist	.394**	.350**	.476**	.456**	.461**	.461**	.475**	.485**	.684**	1.000

Note: **Correlation is significant at the $p < .01$ level (2-tailed).

Appendix D

Mplus Syntax for the Cross-Lagged Panel Model

```
  title: Panel Model Final

  data: file = MPlus_diss.dat;

variable: names =  ID Gender Race FRL IEP Gifted ELL Mobile
                 Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
                 Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg Ref12lg
                 MsState HsState GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
                 Enroll Persist;
                 missing = all(999);
                 usevar = Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
                          Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg  Ref12lg
                          GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
                          MsState HsState
                           gender race FRL IEP gifted ELL mobile;

  analysis: type = general;

  model: att8lg on att7lg; Att9lg on att8lg; att10lg on Att9lg;
      att11lg on att10lg; att12lg on att11lg;
      ref8lg on ref7lg; ref9lg on ref8lg; ref10lg on ref9lg;
      ref11lg on ref10lg; ref12lg on ref11lg;
      GPA8 on GPA7; GPA9 on GPA8; GPA10 on GPA9;
      GPA11 on GPA10; GPA12 on GPA11;
      HsState on MsState;
      MsState with GPA7; MsState with Ref7lg; MsState with Att7lg;
      GPA7 with Ref7lg; GPA7 with Att7lg; Ref7lg with Att7lg;
      MsState with GPA8; GPA8 with Ref8lg; GPA8 with Att8lg;
      Ref8lg with Att8lg;
      HsState with GPA9; HsState with GPA10; HsState with GPA11;
      HsState with GPA12;
      GPA9 with Ref9lg; GPA9 with Att9lg; Ref9lg with Att9lg;
      GPA10 with Ref10lg; GPA10 with Att10lg; Ref10lg with Att10lg;
      GPA11 with Ref11lg; GPA11 with Att11lg; Ref11lg with Att11lg;
      GPA12 with Ref12lg; GPA12 with Att12lg; Ref12lg with Att12lg;
  ! set correlation to 0 for variables you don't want correlated
      HsState on Att12lg @ 0; HsState on Ref12lg @ 0;
  ! cross lag paths for all GPA to behavior all sig
       Ref8lg on GPA7; Ref9lg on GPA8; Ref10lg on GPA9; Ref11lg on GPA10;
       Ref12lg on GPA11;
  ! cross lag paths for all GPA to Attendance all sig
        att8lg on GPA7; att9lg on GPA8; att10lg on GPA9; att11lg on  GPA10;
```

```
    att12lg on GPA11;
! cross lag paths for all Attendance to GPA sig only
    GPA8 on att7lg;
! cross lag paths for all GPA to behavior sig only
    GPA8 on ref7lg; GPA10 on ref9lg; GPA11 on ref10lg;
    GPA12 on ref11lg;
! adding in covariates to the model
     GPA7 on gender; GPA7 on race; GPA7 on IEP;
     GPA7 on gifted; GPA7 on mobile;
     GPA7 on FRL;
     att7lg on race; att7lg on IEP;
     att7lg on gifted; att7lg on ELL; att7lg on mobile;
     att7lg on FRL;
     ref7lg on gender; ref7lg on race; ref7lg on IEP;
     ref7lg on gifted;
     ref7lg on FRL;
     MsState on race; MsState on IEP;
     MsState on gifted; MsState on ELL; MsState on mobile;
     MsState on FRL;
     HsState on gifted;
! adding correlations for covariates
     gender with race; gender with FRL; gender with IEP;
     gender with gifted; gender with ELL; gender with mobile;
     race with FRL; race with IEP; race with gifted; race with mobile;
     FRL with IEP; FRL with gifted; FRL with ELL; FRL with mobile;
     IEP with gifted; IEP with ELL; IEP with mobile;
     gifted with ELL; gifted with mobile;
     Ell with mobile;

output: sampstat stdyx modindices (10);
```

Appendix E

Mplus Syntax for the Enrollment Model

```
title: Enrollment Outcome Analyses

data: file = MPlus_diss.dat;

variable: names =  ID Gender Race FRL IEP Gifted ELL Mobile
              Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
              Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg Ref12lg
              MsState HsState GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
              Enroll Persist;
              missing = all(999);
              usevar = Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
                    Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg Ref12lg
                    GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
                    MsState HsState
                    gender race FRL IEP gifted ELL mobile
                    enroll;
              categorical = Enroll;

analysis: type = general

model: att8lg on att7lg; Att9lg on att8lg; att10lg on Att9lg;
   att11lg on att10lg; att12lg on att11lg;
   ref8lg on ref7lg; ref9lg on ref8lg; ref10lg on ref9lg;
   ref11lg on ref10lg; ref12lg on ref11lg;
   GPA8 on GPA7; GPA9 on GPA8; GPA10 on GPA9;
   GPA11 on GPA10; GPA12 on GPA11;
   HsState on MsState;
   MsState with GPA7; MsState with Ref7lg; MsState with Att7lg;
   GPA7 with Ref7lg; GPA7 with Att7lg; Ref7lg with Att7lg;
   MsState with GPA8; GPA8 with Ref8lg; GPA8 with Att8lg;
   Ref8lg with Att8lg;
   HsState with GPA9; HsState with GPA10; HsState with GPA11;
   HsState with GPA12;
   GPA9 with Ref9lg; GPA9 with Att9lg; Ref9lg with Att9lg;
   GPA10 with Ref10lg; GPA10 with Att10lg; Ref10lg with Att10lg;
   GPA11 with Ref11lg; GPA11 with Att11lg; Ref11lg with Att11lg;
   GPA12 with Ref12lg; GPA12 with Att12lg; Ref12lg with Att12lg;
! set correlation to 0 for variables you don't want correlated
   HsState on Att12lg @0; HsState on Ref12lg @0;
! Cross-lagged paths: Model 1 GPA --> Beh
    Ref8lg on GPA7; Ref9lg on GPA8; Ref10lg on GPA9; Ref11lg on GPA10;
    Ref12lg on GPA11;
```

```
! Cross-lagged paths: Model 2 GPA --> Att
    att8lg on GPA7; att9lg on GPA8; att10lg on GPA9; att11lg on GPA10;
    att12lg on GPA11;
! Cross-lagged paths: Model 3 Att --> GPA
    GPA8 on att7lg;
! Covariates added to model
     GPA7 on gender; GPA7 on race; GPA7 on IEP;
     GPA7 on gifted; GPA7 on mobile;
     GPA7 on FRL;
     att7lg on race; att7lg on IEP;
     att7lg on gifted; att7lg on ELL; att7lg on mobile;
     att7lg on FRL;
     ref7lg on gender; ref7lg on race; ref7lg on IEP;
     ref7lg on gifted;
     ref7lg on FRL;
     MsState on race; MsState on IEP;
     MsState on gifted; MsState on ELL; MsState on mobile;
     MsState on FRL;
     gender with race; gender with FRL; gender with IEP;
     gender with gifted; gender with ELL; gender with mobile;
     race with FRL; race with IEP; race with gifted; race with mobile;
     FRL with IEP; FRL with gifted; FRL with ELL; FRL with mobile;
     IEP with gifted; IEP with ELL; IEP with mobile;
     gifted with ELL; gifted with mobile;
     Ell with mobile;
! Outcome analyses
     enroll on GPA12; enroll on att12lg; enroll on ref12lg@0;
     enroll on HsState;
     enroll on GPA11@0; enroll on att11lg@0; enroll on ref11lg@0;
     enroll on GPA10@0; enroll on att10lg@0; enroll on ref10lg@0;
     enroll on GPA9@0; enroll on att9lg@0; enroll on ref9lg@0;
     enroll on GPA8; enroll on att8lg@0; enroll on ref8lg@0;
     enroll on MsState;
     enroll on GPA7; enroll on att7lg@0; enroll on ref7lg@0;
     enroll on gender; enroll on race; enroll on IEP; enroll on gifted;
     enroll on ELL; enroll on mobile; enroll on FRL;

output: sampstat stdyx modindices (10) tech4;
```

Appendix F

Mplus Syntax for the Enrollment Persistence Model

```
title: Persistence Outcome Analyses

data: file = MPlus_diss.dat;

variable: names =  ID Gender Race FRL IEP Gifted ELL Mobile
           Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
           Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg Ref12lg
           MsState HsState GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
           Enroll Persist;
           missing = all(999);
           usevar = Att7lg Att8lg Att9lg Att10lg Att11lg Att12lg
                 Ref7lg Ref8lg Ref9lg Ref10lg Ref11lg Ref12lg
                 GPA7 GPA8 GPA9 GPA10 GPA11 GPA12
                 MsState HsState
                 gender race FRL IEP gifted ELL mobile
                 persist;
           Categorical = persist;

analysis: type = general;

model: att8lg on att7lg; Att9lg on att8lg; att10lg on Att9lg;
     att11lg on att10lg; att12lg on att11lg;
     ref8lg on ref7lg; ref9lg on ref8lg; ref10lg on ref9lg;
     ref11lg on ref10lg; ref12lg on ref11lg;
     GPA8 on GPA7; GPA9 on GPA8; GPA10 on GPA9;
     GPA11 on GPA10; GPA12 on GPA11;
     HsState on MsState;
     MsState with GPA7; MsState with Ref7lg; MsState with Att7lg;
     GPA7 with Ref7lg; GPA7 with Att7lg; Ref7lg with Att7lg;
     MsState with GPA8; GPA8 with Ref8lg; GPA8 with Att8lg;
     Ref8lg with Att8lg;
     HsState with GPA9; HsState with GPA10; HsState with GPA11;
     HsState with GPA12;
     GPA9 with Ref9lg; GPA9 with Att9lg; Ref9lg with Att9lg;
     GPA10 with Ref10lg; GPA10 with Att10lg; Ref10lg with Att10lg;
     GPA11 with Ref11lg; GPA11 with Att11lg; Ref11lg with Att11lg;
     GPA12 with Ref12lg; GPA12 with Att12lg; Ref12lg with Att12lg;
! set correlation to 0 for variables you don't want correlated
     HsState on Att12lg @0; HsState on Ref12lg @0;
! Cross-lagged paths: Model 1 GPA --> Beh
      Ref8lg on GPA7; Ref9lg on GPA8; Ref10lg on GPA9; Ref11lg on GPA10;
      Ref12lg on GPA11;
```

```
! Cross-lagged paths: Model 2 GPA --> Att
    att8lg on GPA7; att9lg on GPA8; att10lg on GPA9; att11lg on GPA10;
    att12lg on GPA11;
! Cross-lagged paths: Model 3 Att --> GPA
    GPA8 on att7lg;
! Covariates added to model
     GPA7 on gender; GPA7 on race; GPA7 on IEP;
     GPA7 on gifted; GPA7 on mobile;
     GPA7 on FRL;
     att7lg on race; att7lg on IEP;
     att7lg on gifted; att7lg on ELL; att7lg on mobile;
     att7lg on FRL;
     ref7lg on gender; ref7lg on race; ref7lg on IEP;
     ref7lg on gifted;
     ref7lg on FRL;
     MsState on race; MsState on IEP;
     MsState on gifted; MsState on ELL; MsState on mobile;
     MsState on FRL;
     gender with race; gender with FRL; gender with IEP;
     gender with gifted; gender with ELL; gender with mobile;
     race with FRL; race with IEP; race with gifted; race with mobile;
     FRL with IEP; FRL with gifted; FRL with ELL; FRL with mobile;
     IEP with gifted; IEP with ELL; IEP with mobile;
     gifted with ELL; gifted with mobile;
     Ell with mobile;
! Outcome analyses
     persist on GPA12@0; persist on att12lg@0; persist on ref12lg@0;
     persist on HsState;
     persist on GPA11; persist on att11lg@0; persist on ref11lg@0;
     persist on GPA10@0; persist on att10lg@0; persist on ref10lg@0;
     persist on GPA9; persist on att9lg@0; persist on ref9lg@0;
     persist on GPA8; persist on att8lg@0; persist on ref8lg;
     persist on MsState;
     persist on GPA7; persist on att7lg@0; persist on ref7lg@0;
     persist on gender; persist on race; persist on IEP; persist on gifted;
     persist on ELL; persist on mobile; persist on FRL;

output: sampstat stdyx modindices (10);
```