Abstract
High school dropout rates are a concerning trend for educators, administrators, education policy makers, and communities. A promising effort to address dropout rates is an empirical approach known as Early Warning Systems (EWS). The EWS is a prediction model that determines an individual student’s risk of dropping out of high school. The prediction model is designed to alert educators and parents to the risk levels at an early stage to allow interventions to be employed early on in order to shift the trajectory of students displaying risks of dropping out.

Background
When a student drops out of school, it is considered the culmination of a process rather than a single event. (Hammond, Linton, Smink and Dave, 2007). As a process, there are multiple ways to shift the trajectory of a student at risk of dropping out. Unfortunately, these efforts are taken after the process had gained momentum to the point where the outcome cannot be altered.

Early Warning Systems (EWS) or Early Warning Indicators (EWI) are platforms that compile student-level information such as attendance, behavior and academic performance to a statistical model that predicts an individual student’s risk of dropping out of school.

In 2013, 31 states provide some early warning reports (Data for Action, 2013). The most commonly used predictors revolve around the number of absences, behavior and academic or course performance.

Purpose
- Designed to examine the variability within different models and familiarize audience with core elements of a dropout prediction model.
- Model variability will be examined within the individual policy context of states that use different types of models.

Sample EWS Profiles
Maine’s At Risk Data Mart

South Carolina’s Student Potential Performance Snapshot

Sample
- HSLS 09 sample (n=21444) was drawn randomly from a representative sample of 944 public and private high schools.
- Students, parents math/science teachers were asked to complete surveys, in addition to a school counselor and school administrator for each of the 944 schools.
- Random sample of 500 selected from this database for analysis purposes.
- Variables used include: number of absences, number of school suspensions, whether or not the student passed algebra, and whether or not the family income is 185% of the Federal Poverty Line.

Methods
Three hypothetical students were used as case studies of EWS variability.

- Student A: 1 absence, 0-in-school suspensions, successful Algebra passage, Family Income 200% FPL.
- Student B: 4 absences, 2-in-school suspensions, successful Algebra passage, Family Income 150% FPL.
- Student C: 9 absences, 1-in-school suspension, non-passage of Algebra, Family Income 250% FPL.

Three models, utilized in different states, are used to assess the dropout risk presented by an individual student.

- Regression with basic predictors, This model, used by states such as Delaware, includes Attendance, Behavior/Discipline and Course/Test Performance.

Published Equation:
Dropout probability = \( \frac{1}{1 + e^{-(\beta_0 + \beta_1 \times Attendance + \beta_2 \times Discipline + \beta_3 \times TestScore)}} \)

- Regression with expanded predictors: Used by states including Louisiana, this model demonstrates an EWS model with additional one-level predictor in addition to the basic predictors. SES, measured by family income, race, and student’s academic performance, was used as the expanded predictor in the HSLS sample.

Published Equation:
Dropout probability = \( \frac{1}{1 + e^{-(\beta_0 + \beta_1 \times Attendance + \beta_2 \times Discipline + \beta_3 \times TestScore + \beta_4 \times SES)}} \)

- Multi-Level Model (MLM): Utilized by states such as Arkansas, this model has the unique benefit of exploring the effects of concentrated dropout rates within certain buildings by accounting for the nested nature of students within schools.

Published Equation:
Level-1 Model: Dropout Probability = \( B0 + (\text{Intervention} \times B1) + B2 \times \text{Attendance} + B3 \times \text{Behavior} + B4 \times \text{TestScore} \)

Level 2 Model:
\( B0 = G00 + U0 \)
\( B1 = G10 + U1 \)
\( B2 = G20 + U2 \)
\( B3 = G30 + U3 \)

Note: Predictors are dichotomous in the published model. For the purposes of this research, predictors in the HSLS sample were not modeled as dichotomous.

Results
Equations developed using the HSLS 09 sample.

- Basic Regression: \( \logit(p) = -3.56 - 0.040(\text{number of in-school suspensions}) - 0.213 (\text{number of absences}) + 0.078(\text{algebra passage}) \)
  - Note: Using the HSLS Sample: all predictors are nonsignificant at p<0.05

- Expanded Regression: \( \logit(p) = -3.758 - 0.050(\text{number of in-school suspensions}) - 0.220 (\text{number of absences}) + 0.076(algebra passage) - 0.082 \) (poverty 185%FPL)
  - Note: Using the HSLS Sample: all predictors are nonsignificant at p<0.05

- MLM: Predicted Dropout risk = \( \beta_0 + \beta_1 \times Attendance + \beta_2 \times Discipline + \beta_3 \times TestScore \)

Student A
- Basic Regression: \( \logit(p) = -3.56 - 0.040(1) - 0.213 (1) + 0.078(1) - 3.699(1) \)

Hazard of Dropout out of High School: 2.48%

Expanded Regression: \( \logit(p) = -3.758 - 0.050(-2.224) + 0.076(1) - 0.082 (0) - 3.902(1) \)

1.98% Chance of Dropping out of High School

Student B
- Basic Regression: \( \logit(p) = -3.56 - 0.040(1) - 0.213 (1) + 0.078(1) \)

Hazard of Dropout out of High School: 0.21%

Expanded Regression: \( \logit(p) = -3.758 - 0.050(-2.224) + 0.076(1) - 0.082 (0) - 3.902(1) \)

0.5% Chance of Dropping out of High School

Student C
- Basic Regression: \( \logit(p) = -3.56 - 0.040(1) - 0.213 (1) + 0.078(1) \)

Hazard of Dropout out of High School: 0.21%

Expanded Regression: \( \logit(p) = -3.758 - 0.050(-2.224) + 0.076(1) - 0.082 (0) - 3.902(1) \)

0.5% Chance of Dropping out of High School

Significance
As the proliferation of EWSs occurs throughout states and districts, it is increasingly important to understand how these predictive tools vary depending on student characteristics and policy contexts. There has not yet been a comprehensive and quantitative assessment of Dropout of EWSs across regions and school systems. Although there is some overlap in variables shown to have predictive power across multiple models, different populations and policies mandate the inclusion of different variables in the model. This explains the presence of variables like community school attendance in only some models while standardized test scores are more prevalent across models.

Our study highlights the differing potency of variables in predicting dropout in different populations. This study demonstrates that, despite the variability in states’ models, EWSs should be viewed as empirically sound tools to support and inform intervention policies.

Discussion
Since the term “dropout factory” (Balfanz & Legters, 2004) became part of the public lexicon, states and local governments have experienced mounting pressure to identify not only the risk factors associated with dropout but to produce the data by which schools can be identified. High school completion is seen to be a valuable measure of student achievement for several reasons: it is an unambiguous measure of student attainment, it is relatively simple to compute given graduation rates of similar populations, and late graduates cost their locales more in terms of intervention and remediation (Knowles, 2014). Conversely, on-time high school graduation is related to a constellation of benefits for individuals and communities ranging from psychological well-being, greater earning power, and increased financial stability. State, local, and school-level administrators began to be held accountable for discerning which educational programs and initiatives increase student persistence and high school completion. Policy and governance structures in some states reflect this pressure. In Delaware, for example, the state’s Department of Education formed the Delaware Promise Dropout Prevention Subcommittee. The purpose of this subcommittee was to deploy America’s Promise grant funds in pursuit of a functional and accessible dropout early warning system. As of 2013, Delaware is just one of 31 states that provide some early warning reports (Data for Action, 2013). In 2011, there were 18 states providing reports of this nature. However, there is still great need for early warning systems that provide information about risk factors to a number of stakeholders that may include students, parents, guidance counselors, teachers, administrators, and policymakers. Also, despite the progress states have made in generating risk assessments, there needs to be greater attention paid to programmatic failures. That is, early warning systems need to identify whole schools, districts, or regions that fail to support students’ high school completion.

References

Contact Information
- Lauren P. Bales: baules.11@osu.edu
- Lauren M. Porter: porter.700@osu.edu