Emerging SLDS Research:

Montana Early Warning System

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National Center for Education Research 'Using SLDS' Grant

Montana Statewide Longitudinal Data System

Montana Office of Public Instruction

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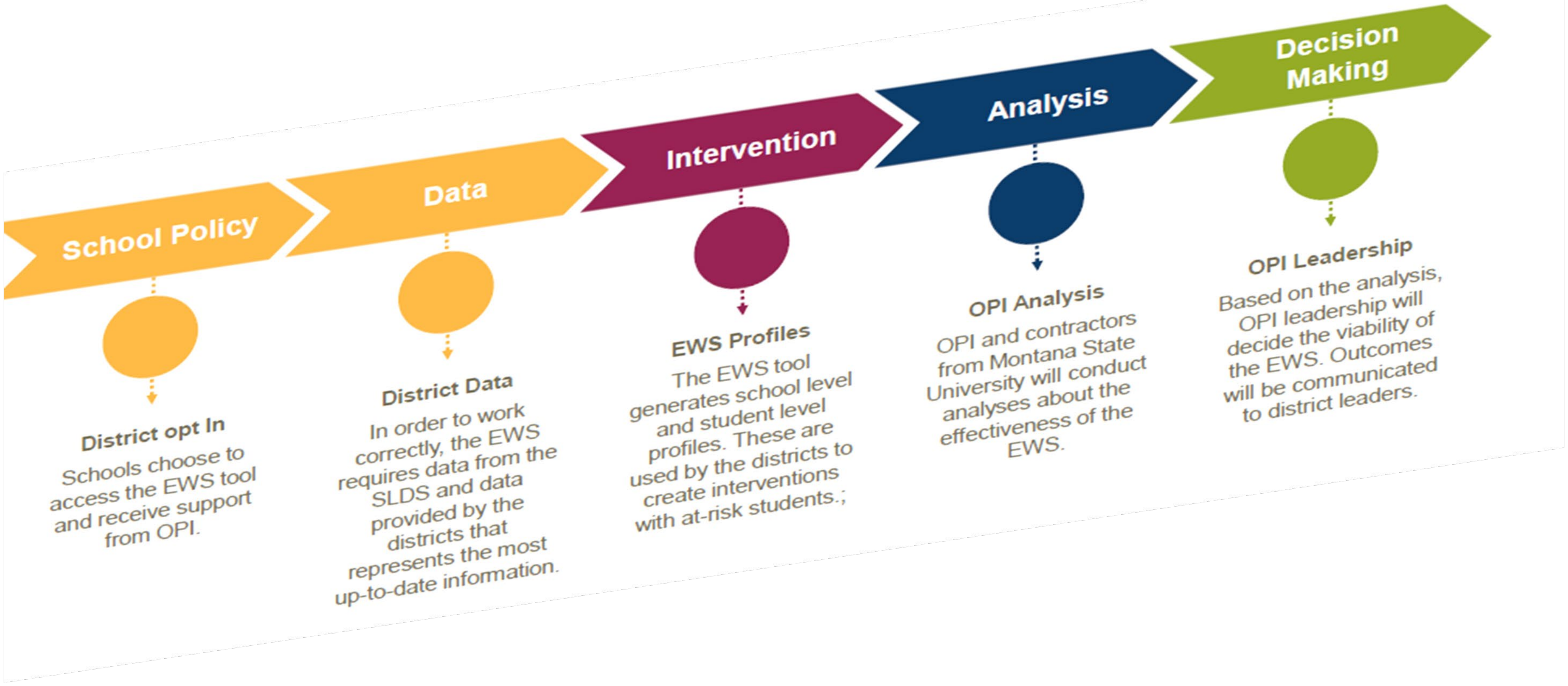
Scope of Montana SLDS Research

- **Internal Research as requested by leadership.**
  - Salary
  - Turnover
  - Professional Development
  - Assessment
- **Targeted support to research contractors:**
  - University of Montana
  - Montana State University
- **Grant supported research (Institute of Education Sciences)**
  - Montana Early Warning System
  - School level poverty measures



Montana's Early Warning System

Articles: AASA Journal of Scholarship and Practice (https://www.aasa.org/resources/resource/Under-the-hood) and American School Board Association (https://www.nsba.org/ASBJ/2024/august/early-warning-system)

Articles in Review: Education Policy Analysis Archives and Discover Education

Early Warning Systems Provide a Tool to Identify Students at Risk of Dropping Out

- Early Identification is the first steppingstone of the model
- Focus is on relationship building, development of a data culture, tying data to intervention, tools for longitudinal analysis, and progress monitoring.
- Indicators factor in attendance, behavioral, and academic data.
- By 2013, they became popularized in Statewide Longitudinal Data Systems (funded by the National Center for Education Statistics).
- Data on the effectiveness of Early Warning Systems is sparse. It is largely limited to an analysis of algorithms and the focus on early identification. There is little research beyond 2015.

Montana EWS Program

gems

gems.opi.mt.gov

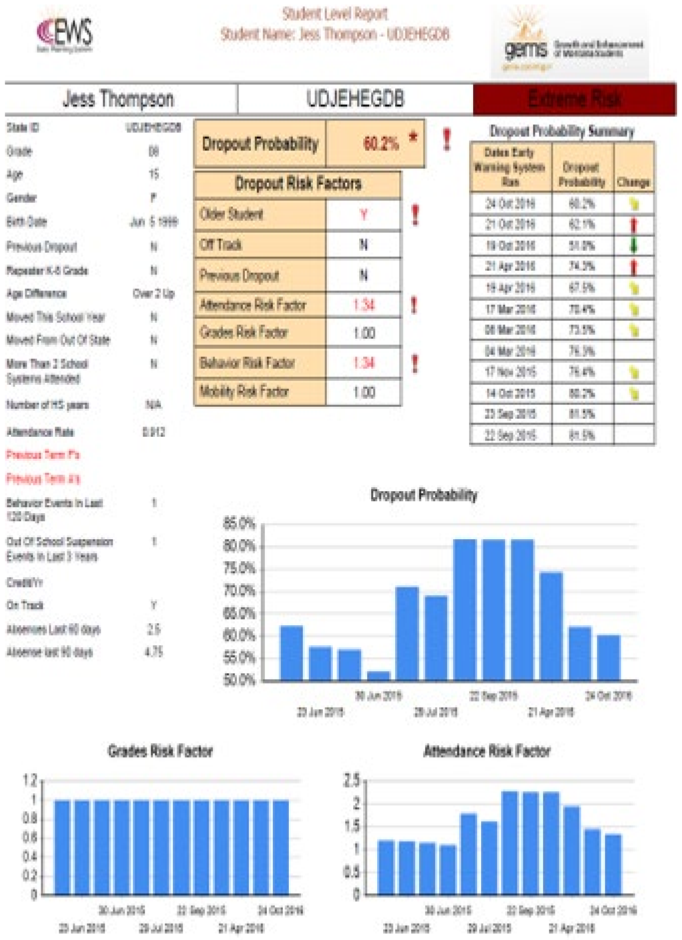
Goal 1: Create and maintain a statistical model that accurately predicts the odds of a student dropping out (model development).

Goal 2: Identify at-risk students before they drop out (involves professional development by the OPI).

Goal 3: Help schools that opt-in to the program to identify factors that are impacting each student's dropout risk to prioritize and target interventions according to individual needs and school priorities (involves professional development).

Goal 4: Help schools understand dropout risk trends at the school level to make decisions regarding policy that may influence dropout risk (professional development).

The Online Tool



School level report - Summarizes data and creates visualizations for school level dropout risk, and specific trends including grades, attendance, behavior, and mobility.

Student summary report - Generates a spreadsheet containing all student data for the school, including risk rankings, percentage risk, change in risk, and odds ratios for specific risk factors.

Student detail report - Provides data and visualizations for a single student within that school, including their current dropout risk, change in risk over time, information on missing data, and predominant risk factors where interventions may be warranted.

* Data in graphic is FERPA compliant as it does not represent actual student data.

Research Procedures

- **Task 1**: We know the ability of the model to predict dropout. Hence, we investigate the propensity of the model to predict graduation to gauge the efficiency of the model.
- **Task 2**: We investigate the degree of implementation of the model in schools. Has access to EWS data inspired policy and increases in student supports?
- **Task 3**: We focus on how robust the student outcomes are in these schools and the impact of dropout interventions on graduation and postsecondary enrollment.

What may have impacted student outcomes (mediating factors)

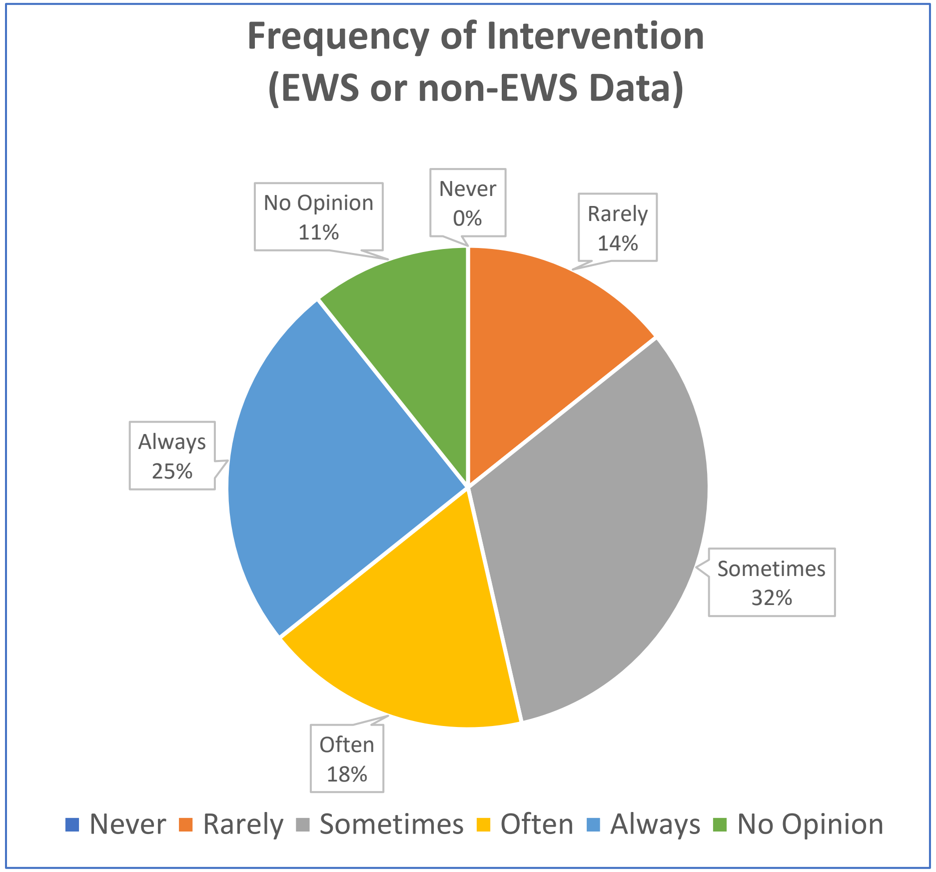
Relationship building is frequently mentioned in the data. This process helps student engagement by providing role models (characteristic of Tier 3 interventions)

Stakeholders focus on how far tool may take you.
High adoption schools view that they know students better given the insights of the tool.

- Ability to find spots in which the greatest impact can happen with each student.
- Vision is important, and that vision should come from a centralized source and be shared.
- Formal mechanisms, such as MTSS processes, are a characteristic of high adoption.

High adopters tend to disseminate EWS data to all stakeholders, including teachers. Dissemination was highly localized and in high adoption schools was designed to meet counselors and teachers' needs. Stakeholders find the tool easy to communicate and let data turn into formal and informal conversations.

Progress Monitoring and Follow-up are Key Components of EWS



- **In Montana, those schools that have been in the EWS program the longest tend to have formal procedures for follow-up.** This trend is also significantly more frequent than schools that began after 2015 (p=0.021).
- Schools focus on early identification, which shows the interest and data use about the tool.
- **Fewer districts focus on ongoing progress monitoring. Monitoring, and the ability to adjust interventions based on data, is a sign of a well-developed data culture.**

How did EWS predictions compare to final dropout rates?

4-year graduation rate based on 9th grade cohorts from AY 2009-2010 to AY 2017-2018; students with an EWS score			
	Average EWS dropout prediction (p)	Implied EWS graduation probability (1-p)	Actual graduated on time
Students ever scored at extreme risk of dropping out (N=5,843)	35.6%	64.4%	62.6%
Students ever scored at risk of dropping out but never at extreme risk (N=5,068)	9.8%	90.2%	90.1%
Students never flagged as at risk (N=18,517)	1.9%	98.1%	97.0%

- In the survey and interviews, stakeholders identified that among all identified students (at risk and extreme at risk), **at least 75% of students graduate or go on to the next grade.**
- **The EWS scores are strongly associated with eventual dropout.** EWS scores indicate a higher probability of dropout than happens each year for the student, implying that schools that use the system will be alerted in advance of student dropout.

How well does EWS predict dropout rates?

Very accurate: 1 % increase in average EWS score → 1.07% increase in actual dropout

That is the average of *all* the student scores—scores tend to go closer to dropout event

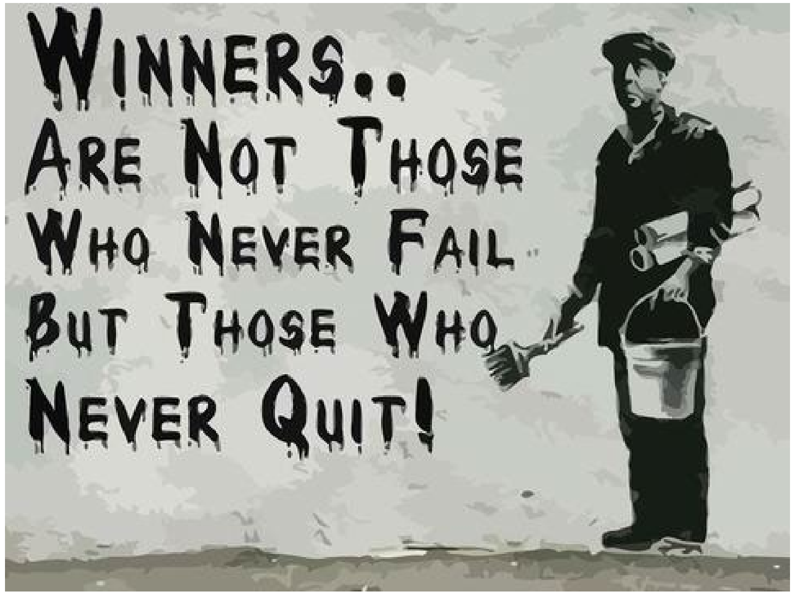
Slightly underpredicts dropping out for

- Male students (1% increase in EWS probability → 1.1% increase in actual dropout)
- White students (1% increase in EWS probability → 1.08% increase in actual dropout)
- Hispanic students (1% increase in EWS probability → 1.1% increase in actual dropout)

Very accurate for female, Native American students

Targeting Resources: Analysis of Cost

“So much time is spent during the administrative work. EWS does it for you and the results are more consistent and insightful with a diagnostic tool that is focused, and evidence based.”



First Efficiency is Early Identification: One principal commented that ***costs are minimal per student, but costs would be higher if they didn’t have the EWS data or the ability to target resources.***

- Interventions cost less when students are identified early.
- Costs/student goes down.
- Overall costs stay the same as program expands (more students receiving support or intense supports).

Administrative Overhead to Collect and Manage Data Goes Down

- Schools report that they must look at over five different data systems to get a view of the same data.
- Savings from the enhanced communication among staff drive costs down

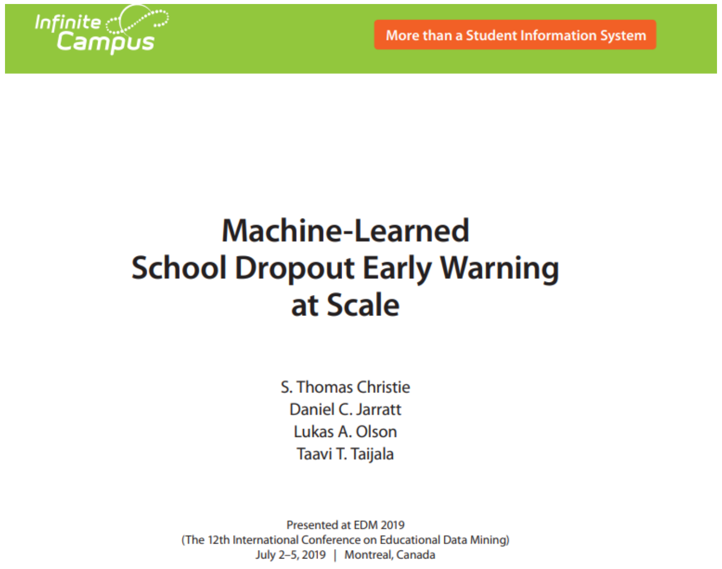
Comparing EWS Options – Montana Early Warning System (OPI)

- **Type of metric:** Overall dropout risk score and risk level. Students with a predicted dropout probability of 15 percent or more are flagged as "At Risk," and students with a predicted probability of 40 percent or more are flagged as "Extreme risk." Student indicators are coded relative to thresholds using red, yellow and green arrows that show the trajectory.
- **Score calculation:**
  - The underlying risk model is Montana specific. The model is calibrated each year using Montana data from participating schools in a logistic regression model.
  - The current indicators used in the model include uses attendance, grade retention, moves across schools, and behavioral incidents (like suspensions or expulsions). These are used to predict dropout probabilities for students in 3rd through 12th grade. The score uses historical data for a student as well as current data. The model does not include race or gender of students.
  - The model generates reports with many ways to assess students, including reports on the percentages of students at the school in each of these risk categories, the percentage flagged for grades, attendance, or behavioral risk factors, comparisons with the state, and comparisons with previous periods. Individual student reports show the student's current dropout probability along with their history of scores, with colored flags for high risk factors and arrows that indicate rising or falling risk probabilities.
- **Model transparency:** Because the model is produced by OPI, there is more transparency about the scores are calculated.
- **Validation:** Researchers have validated the accuracy of this EWS both overall and for racial and gender subgroups (Hill, Stoddard, & Clausen, 2024).
- **Cost and Ease of Use:** Users must upload student data to use the system. OPI provides training and support. Free to districts, but currently is in use in a small set of districts.

Infinite Campus EWS

- **Type of metric:** Individual student "grad score." The platform default is to designate students who fall below the 5th percentile of all scores as being at "high risk" for failing to graduate, while students in the 5th-20th percentile are flagged as "medium risk."

- **Score calculation:**
  - The machine learning model was initially developed using data on 6 million student-years of education records across 32 states. Currently, more than 150 million student-years of data are used in the model.
  - Infinite Campus reports that the scores are based on the ABC's (attendance, behaviors and course performance) as well as "stability" that measures household and enrollment stability. Currently, there are **75 different factors used in the model**. The model also includes race and gender.
  - Risk prediction is automated based on the data in the Infinite Campus platform. Scores are automatically generated on a daily basis, reflecting new information about absences, grades, and disciplinary information. Data for all student years in the system are included.
- **Model transparency:** The high complexity and the proprietary nature of the model limits the tool's transparency.
- **Validation:**
  - It has been validated as highly predictive of dropout risk, although this assessment was performed by Infinite Campus researchers (Christie et al 2019).
  - Infinite Campus's tool is currently used in all districts in Nevada, Delaware, Kentucky, North Carolina, South Dakota, and Hawaii. Nevada recently used the system to allocate state funding.
- **Cost and Ease of Use**: The grad score calculation relies on the data that is already a part of the Infinite Campus system. To use, districts must pay for the Campus Analytic Suite.


Infinite Campus
More than a Student Information System

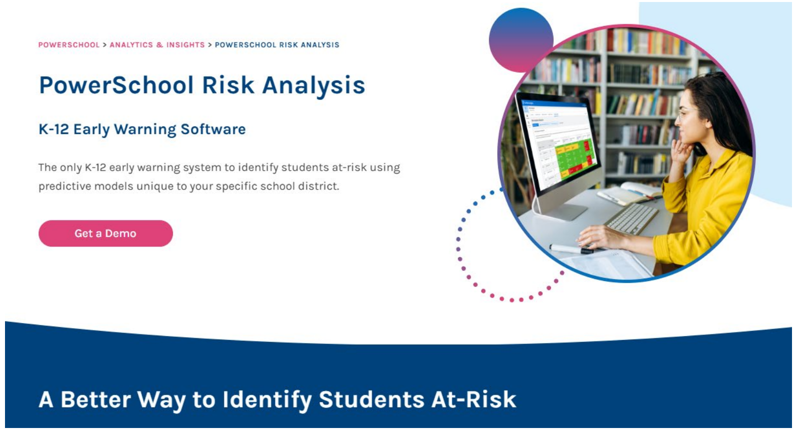
Machine-Learned
School Dropout Early Warning
at Scale

S. Thomas Christie
Daniel C. Jarratt
Lukas A. Olson
Taavi T. Taijala

Presented at EDM 2019
(The 12th International Conference on Educational Data Mining)
July 2–5, 2019 | Montreal, Canada

Power School Risk Analysis

- **Type of metric:** The PowerSchool site I accessed uses a "Threshold" based model, flagging students with an indicator above or below a set target. "At risk" students are those with one or more flag. Based on the test site I was able to access, both high schools and middle schools can see lists of "At risk" students.
  - However, on the PowerSchool website (https://www.powerschool.com/insights/risk-analysis/), it appeared that there is an option for graduation probability scores. It also appeared that there was an option for including state assessments in the risk scores. These were not on the demo site.
- **Score calculation**: On the demo site I accessed, alerts are triggered when a specific threshold is crossed. For example, the attendance alert default is to flag students who have missed 2 or more days in a term.
- **Model transparency:** PowerSchool does not appear to use a formal model, other than to set the cutoffs. However, these cutoffs are easily visible. I did not find documentation about how the graduation prediction model that appeared on the website might operate.
- **Validation:** I did not identify any studies providing evidence about PowerSchool's tool.
- **Cost and Ease of Use:** PowerSchool relies on the data that is already in the system and does not require additional work.



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Data Warehouse: https://gems.opi.mt.gov

Data Use: https://opi.mt.gov/Leadership/Data-Reporting/Research-Portal