

Montana's Early Warning System

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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.



Montana EWS Program



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 (professional

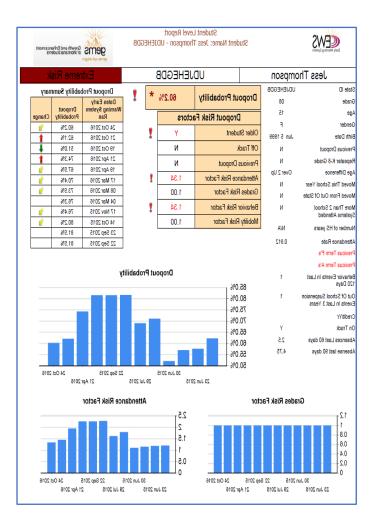
development).

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 (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.



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.



Defined Need – School Context

Trends regarding the ACT Composite average are significant (p = 0.020) and show that the nonadoption group scores higher (19.54) than the low adoption schools (18.54) and medium to high adopters (18.72).



- Cohort graduation rates were higher (93.21%) among non-adopters in comparison to 86.50% among low adoption schools and 86.24% for medium to high adoption schools (p = .001).
- Satisfactory Attendance rates are also higher among nonadopters (49.24%) in comparison to low adoption schools (40.39%) and medium to high adopters (40.16%).
- The Spatially Interpolated Demographic Estimate for these schools was significant (p = .002). In medium to high adoption schools (247.96), there is significantly more economic disadvantage than in low adoption schools (257.50) and with non-adopters (267.60).
- Significant trends are seen with **teacher tenure** in schools (p = 0.012). Experienced teachers are a measure of the quality of instruction. Teachers in medium to high adoption schools have longer tenure than the other groups.



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.

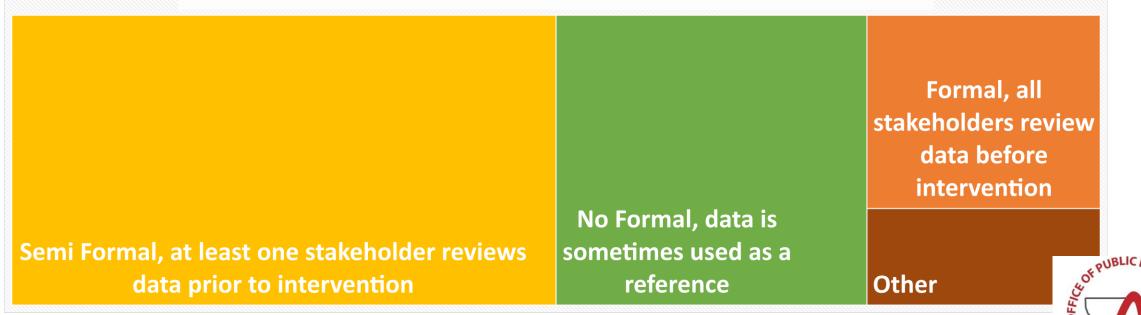
- Ability to find spots in which the greatest impact can happen with each student.
- Vision is important, and that vision should come from a centralized source and be shared.
- Formal mechanisms, such as MTSS processes, are a characteristic of high adoption.

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.

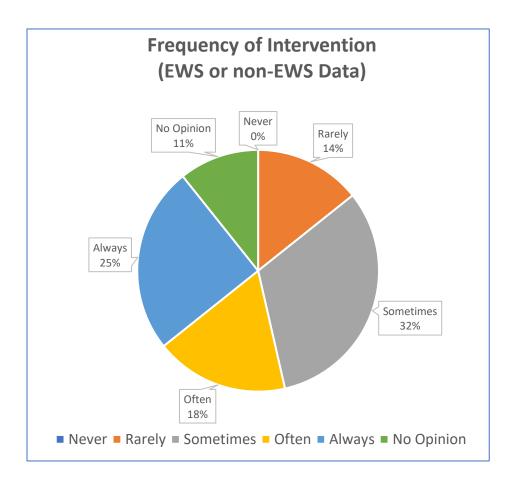


Dissemination

- Formal, all stakeholders review data before intervention
- Semi Formal, at least one stakeholder reviews data prior to intervention
- No Formal, data is sometimes used as a reference
- Other



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.



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."



The 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

Empirical Analysis

Montana OPI provided student and school level data from 2007/08 to present

Student level data is richer for EWS schools than non-adopting schools

Analysis focuses on pre-pandemic period



Empirical Analysis

Main questions:

- 1. Which schools adopted EWS and how much do they use it?
- 2. How accurate are the EWS predictions?
- 3. Does use of EWS improve graduation outcomes?





Number of high schools using EWS by year

Academic year	Number of high schools using EWS system	Number of high schools using EWS system for at least 30% of their students	Number of high schools using EWS system for at least 90% of their students
2011-2012	0	0	0
2012-2013	12	12	11
2013-2014	14	14	11
2014-2015	15	13	7
2015-2016	56	21	18
2016-2017	27	24	22
2017-2018	25	22	21
2018-2019	43	31	27
2019-2020	27	25	22



Number of loads into EWS by year

Academic year	Number of high schools using EWS system	Mean number of school- level loads into EWS	Modal number of school-level loads into EWS
2012-2013	12	14.5	14
2013-2014	14	11.1	18
2014-2015	15	2.0	2
2015-2016	56	6.5	9
2016-2017	27	5.4	4
2017-2018	25	6.1	8
2018-2019	43	5.3	4
2019-2020	27	6.3	8

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Comparison of EWS and non-EWS high schools (N=185)

Academic year	School characteristic	High schools that used EWS	High schools that did not use EWS
2012-2013	Mean number of students	715	224
2012-2013	Share White	0.67	0.79
2012-2013	Share AIAN	0.23	0.13
2012-2013	Share Econ. Disadv.	0.48	0.40
2019-2020	Mean number of students	362	233
2019-2020	Share White	0.62	0.77
2019-2020	Share AIAN	0.25	0.10
2019-2020	Share Econ. Disadv.	0.56	0.46



How well do EWS Scores Predict Dropout?

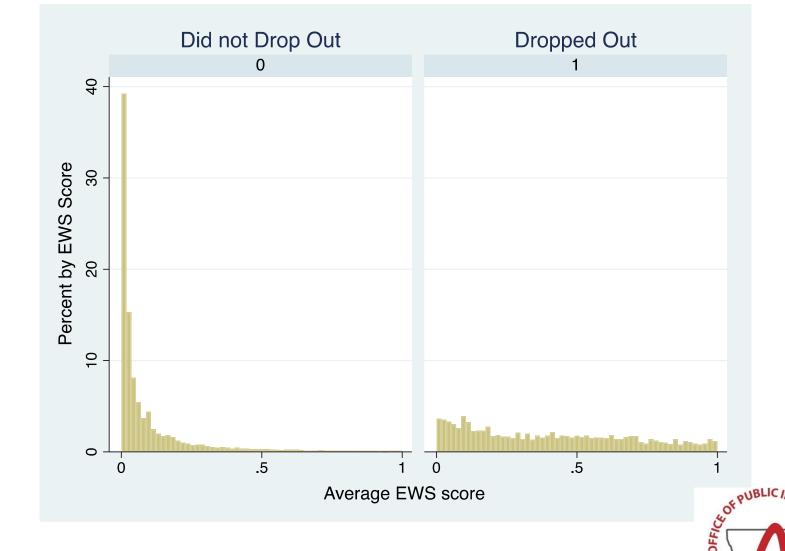
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Frequency of specific scores by eventual dropout status



How well did EWS predict 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

	Graduated on time
Students ever scored at extreme risk of dropping out (N=5,843)	62.6%
Students ever scored at risk of dropping out but never at extreme risk (N=5,068)	90.1%
Students never flagged as at risk (N=18,517)	97.0%
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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%



Model to assess predictive accuracy of EWS

 $Drop_{\{ist\}} = \alpha_0 + \alpha_1 EWSPP_{\{it\}} + \alpha_2 X_{\{it\}} + \lambda_s + \delta_{c,g,t} + \epsilon_{\{ist\}}$

- $Drop_{\{ist\}} = 1$ if drop out in year t
- $EWSPP_{it}$ EWS predicted probability across all years observed
- X background characteristics of students and schools
- λ_s school fixed effects -- control for all factors in common to a school
- $\delta_{c,g,t}$ cohort year and grade fixed effects --account for changes that affect all students in year t, in grade g, and in cohort c
- Standard errors are clustered at the school level
- α_1 the relationship between predicted probability and the actual graduation outcome.

=1 if model perfectly predicts dropout outcomes.



	Ever drop out (Only st	udents with EWS score)
EWS predicted dropout probability: time-varying,	0.833***	
year-to-year	(.031)	
EWS predicted dropout probability: mean over all		1.067***
years		(0.022)
Female	-0.010***	-0.011***
	(0.003)	(0.003)
Hispanic	0.029***	0.014
	(0.009)	(0.010)
Native American	0.061***	0.027***
	(0.011)	(0.009)
Asian	-0.029***	-0.024**
	(0.006)	(0.010)
Black	-0.002	0.003
	(0.016)	(0.018)
Other race category	0.051***	0.035***
	(0.011)	(0.010)
Unit of observation	Student-year	Student
Fixed effects	School, Cohort entry year, grade,	School, Cohort entry year, grade,
	school year	school year
N	79,053	29,056

Does EWS score have same predictive relationship for different demographic groups?

EWS score interacted with	
Female	-0.058**
	(0.029)
Hispanic	-0.007
	(0.082)
Native American	-0.054
	(0.044)
Asian	-0.251
	(0.212)
Black	-0.013
	(0.173)
Other	0.001
	(0.051)

How well does EWS predict dropout rates?

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

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

Slightly underpredicts for male students

Same score for male and female students—female student is about 6 percent less likely to drop out.



Did Using EWS improve graduation rates?

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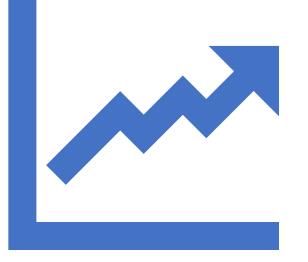
How did dropout rates compare for students in EWS adopting and non-adopting schools ?

4-year graduation rate for cohorts entering 9 th grade AY 2009-2010 to AY 2017-2018			
	Graduated on time		
All students (N=116,053)	87.2%		
Students with any EWS score (N=29,428)	89.0%		
Students never with an EWS Score (N=86,625)	86.6%		
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BUT—Graduation rates have trended up over time

Graduation rates would tend to be lower in the years before the EWS system even began

Students with EWS scores are in later years
→The difference in dropout rates would overstate how effective the EWS is





BUT—schools that adopt EWS differ from non-adopters

If EWS adopting schools are better resourced or tend to have had lower dropout rates

→The difference in dropout rates would overstate how effective the EWS is

On the other hand If EWS adopting schools had more concerns about high dropout rates, the difference across adopting and nonadopting schools would understate how effective the EWS is





Comparison of EWS and non-EWS high schools (N=185)

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How to account for these differences?

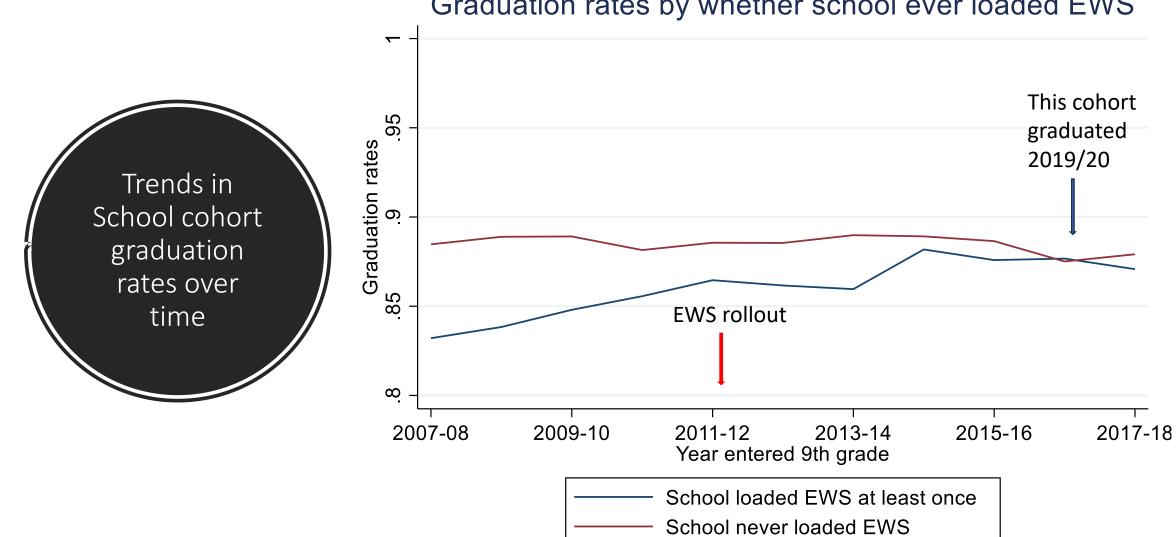




Compare changes in dropout rates for schools that did and did not adopt the system. Do the adopters see bigger declines in dropout rates? Compare students who were exposed to the EWS in more/fewer years. Do students with more exposure have lower

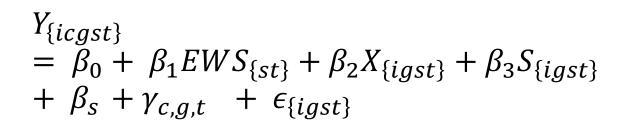
dropout rates?





Graduation rates by whether school ever loaded EWS

Assessing effect of EWS use on graduation



 Y_{icgst} measured as cohort graduation status or year enrollment end status

- EWS_{st} = 1 if school s ever used the EWS system in academic year t Or if student loaded into EWS system
- X controls for student race and gender, school size, Title I school, school free lunch and race shares
- β_1 effect of the school's EWS use on the respective student outcome.



Overall effectiveness of EWS: Student level

		Ever graduate (9th gra	de cohorts from AY 2007-
		2008to AY 2017-2	018; All MT students)
Student loaded into EWS: time-	0.009	0.026***	
varying, year-to-year	(0.007)	(0.04)	
Share of years student loaded			0.023***
into EWS			(0.006)
Female		0.029***	0.017***
		(0.001)	(0.001)
Hispanic		-0.055***	-0.019***
		(0.006)	(0.004)
Native American		-0.146***	-0.046***
		(0.007)	(0.006)
Asian		0.048***	0.023***
		(0.004)	(0.005)
Black		-0.030***	-0.020**
		(0.009)	(0.010)
School controls	None	School enrollment, share fer	male, share of each racial/ethnic
		group, sha	re FRPL, Title I
Unit of observation	Student	St	udent
Fixed effects	Grade, cohort entry year, year	School, grade, cohort entry year, year	
N		10	6,092

Year-to-year effectiveness of EWS: enrollment end status

	Stayed in school	Other enrollment end status	Dropped out	Graduated (12 th grade students only)
Student loaded	0.011***	-0.003***	-0.014***	0.036***
EWS: time-varying,	(0.002)	(0.001)	(0.002)	(0.006)
year-to-year				
		N		N
Student controls	Y	Y	Y	Y
School controls	Y	Y	Y	Y
School, cohort,	Y	Υ	Y	Y
year, grade fixed				
effects				
Unit of observation	Student-year	Student-year	Student-year	Student-year
Observations	917,305	917,305	917,305	97,085
R-squared	0.739	0.046	0.049	0.050

Overall effectiveness of EWS at school level: Cohort graduation status

	Ever graduate (9th grade cohorts from AY 2007 AY 2017-2018; All MT students)	
School loaded EWS: time-varying, year-	0.004*	
to-year	(0.002)	
Share of years school loaded EWS		-0.003
		(0.005)
Student controls	Y	Y
School controls	Y	Y
School, cohort, year, grade fixed effects	Y	Y
Unit of observation	Student-year	Student
Ν	917,388	106,092

Conclusions: Processes

We conclude that the EWS model did work as intended. The degree of EWS implementation is localized and based on multiple interrelated factors. *The core of these factors is how the district finds value in the data and what they decide to do with the data.* Given the scope of these factors, OPI support was seen as a catalyst to school level change.



The rollout of the program reflected a staged process which focused on professional development for high adoption schools in addition to the online tool. The design of the tool was found to be adequate, like online tools associated with the MAPS test administration. The tool was found to be accurate among users.

Scale should meet identified need and capacity for the program to be successful. Some schools do not have a defined need for the program, others do not have the priorities. *At the state level, the scope of the program (access to tool among all kinds of adopters) has eclipsed.* This allows us to focus on existing schools (Professional Development).

Scale, capacity, and priorities will continue to inform school level implementation and information future rollout of the EWS program.



Conclusions: Outcomes

- The EWS is an effective way to identify students at risk of dropout, with scores that are highly associated with actual behavior
- Schools that use the EWS tend to be larger and have more disadvantaged student populations
- Although these schools on average tended to have lower graduation rates, students with EWS scores were more likely to graduate
- The more a student had been in the EWS, the larger the effect.
- It appears that the EWS helps school identify students in most need of extra support.



Contact

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