Research Article

Under the Hood: Montana Early Warning System

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Abstract

Policy research established that it is possible to predict a student will drop out of school based on academic, attendance, behavior indicators. Little is known about the processes that put Early Warning Systems (EWS) in place. This case study of the Montana EWS describes the characteristics of a statewide implementation, the efficiency of the EWS to predict graduation, and effectiveness of the tool among adopters. By painting a picture of high adopters, low adopters, and non-adopters, we can distinguish the demand for the use of the tool, how users respond to the Montana EWS, how the tool is used to intervene with students, and what are the outcomes for the schools that use the tool. Students in high adoption schools who received an EWS score are more likely to graduate in comparison to students in low adoption schools.

Key Words

early warning system, data, state policy, National Center for Education Research

Introduction

The spread of Early Warning Systems (EWS), diagnostic tools used in dropout prevention, reached their tipping point in 2012 following policies tied to dropout prevention, a focus on graduation in federal legislation and SEA accountability systems, and a plethora of research articles that normed various risk factors using common metrics and supports (Bruce, M, Horning Fox, J., & Balfanz, R., 2011; Heppen, J. & Therriault, S.B., 2008; Jerald, 2006). In 2012, Montana focused its attention on developing an early warning system to address issues in drop out and graduation.

Over the next decade, Montana progressively rolled out its early warning system, from a three-year pilot stage. It gained an important online presence. Montana also began to focus on the scale of the program and adoption based on an opt in model. This factor is important as some districts committed to the processes once they found the value of the innovation and corresponding vision (high adoption). However, many districts investigated the EWS and eventually decided against participation (low adoption). There was no system wide mandate.

This case study provides evidence for EWS processes as elaborated in the Montana EWS. The study asks the following research question: what does the implementation of the Montana EWS tell us about the processes involved in framing any EWS? In this article, we look under the hood of the Montana EWS model by noting successes and challenges of the model. In the case of early warning systems, research is underdeveloped about processes and outcomes. (Faria, A. M., Sorensen, N., Heppen, J., Bowdon, J., Taylor, Eisner, R., & Foster, S., 2017; Marken, A., Scala, J, Husby-Slater, M. & Davis, G., 2020).

Through investigating the success and challenges of the Montana EWS model, this case study provides a reference for other local and state implementations that use an opt in model to encourage adoption of the early warning system tool.

The spread of the Montana early warning system became focused on schools of various sizes, with different student information systems, and that have different scope to their dropout prevention processes. There was variation in their implementation strategies and to different degrees schools focused on what longitudinal data could reveal about student progress.

Prior to this research Montana had sparse and unclear evidence to the degree of implementation and the patterns of data use among schools that used Montana EWS diagnostic tools. We knew little about the processes involved in creating and maintaining an EWS. By extension, we also knew little about school level interventions. The efficiency of the tool (defined as its ability to predict dropout and graduation) and the effectiveness of the school level interventions as seen in change in graduation rates is also relevant to our study of the Montana EWS.

The diagnostic tool creates profiles for school and students. The Montana Office of Public Instruction (OPI) provides professional development about the use of the data and provides insights into what triggering events will start, revise, and end an intervention. The principal element of the diagnostic tool is the interface that users see with the results of the logistic regression analyses.

The Montana EWS reports include:

- **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**
  All student EWS 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.

The EWS team at the Montana Statewide Longitudinal Data System (SLDS) consists of a Database Administrator, a Data Coach, and a Research Analyst. This team coordinated the efforts of the OPI to maintain the EWS and related professional development activities.

The author works closely with the SLDS but has little involvement with Montana EWS program. In addition, researchers at Montana State University participated in this evaluation of the Montana EWS helping OPI complete a National Center for Education Research grant that promotes the effective use of statewide longitudinal data system data in many states.

The goal of this research is to investigate the processes used to implement the tool and target interventions, efficiency of the tool to predict graduation, and an analysis of graduation to gauge the impact of districts efforts after implementing the program.

Discussions about non completers of K-12 education revolve around individual or systemic failure. The reality of the matter is that dropping out can result from both conditions, of which some factors are more under the control of educators than others.

The incidence of dropout is seen as having a series of individual and societal outcomes that raise the importance of the issue. Median earnings of families headed by a high school non-completers declined by a third between 1974 and 2004 (Jerald, 2006). This aggregates to have an impact on the larger economy. In 2009 it was estimated that there was a 2 - 4% decrease in Gross Domestic Product due to the individual and societal costs of dropout (Bruce et al., 2011).

An EWS is designed to identify a problem, for example defining which areas a student may be at-risk. EWS provides data for early identification of a problem. EWS also provides data to support an intervention across its life cycle. For a student this may manifest in different ways.

The Montana EWS identifies four areas in which a student is struggling (academics, attendance, behavior, and mobility). By identifying early, schools can target an intervention by clearly defining its scope and intensity. Also, schools can allocate resources and support to those students most in need or to those in which an intervention would have the greatest impact.

Progress monitoring demonstrates the depth of an intervention. By using longitudinal data about a student, schools can establish thresholds for continuing, revising, or discontinuing an intervention.

Montana’s model is built on extensive research about EWS indicators across the country. The spread of statewide early warning systems over the past decade was promoted by the Institute for Education Sciences. One of the main benefits to such systems is that it saves time.

Principals and counselors are freed to spend more time with the students, more time monitoring interventions (using EWS tools to monitor interventions) and more time focusing on root causes and potential outcomes of each student's circumstances. With an EWS there are less administrative costs. Working without an EWS takes time. Often this involves juggling multiple data systems when accessing attendance, coursework information, and behavioral data.

The Montana EWS provides data to participating districts using data originated from a centralized data warehouse that is customized, out of the box data, that districts do not have to centrally manage. Moreover, the Montana EWS is not tied to a vendor and is free of cost. Using an EWS represents a culture shift towards data driven success and improvement. According to one superintendent's advice for people using the system, data system managers should make it manageable, make it meaningful, make it matter (Bruce et al., 2011).

Most Early Warning Systems incorporate multi-level logistic regression (Koon & Petscher, 2015). Coherence is gained by focusing on a small number of objective, evidence-based risk factors.

Transparency is furthered by using this small set of risk factors in a manner that is understandable for end users—the school teams which identify thresholds for interpreting the data, the requirements of a decision to intervene with a student, and along the course of the intervention lifecycle, the data needed to make the intervention successful. Logistic regression uses multiple predictors is a hierarchical manner that each shed light on a binary outcome variable. In doing so, the model produces a log of odds for the likelihood of achieving one of the two categories selected for an outcome.

In Montana, the model produces two sets of indicators. First, calculations are made for each risk factor providing odds ratios (attendance, behavior, academics, and mobility). Second, regressions identify an overall dropout probability for each student (the likelihood a student will drop out).

EWS programs can succeed when there is a clear tie between the data and the intervention. There are many ways to make intervention the core of local implementation models. Leadership and vision are local factors that can be enabled by SEA policies.

The hallmark of a successful EWS is that there is an identified need and clear leadership. Moreover, when leadership is directed and transparent, there is a focus on the direct results of the data use, the tying of data to intervention. This involves dissemination of the EWS predictive analytic data to all stakeholders.

Local validation of data is important since this is the context in which decisions about interventions are made. In many cases the focus of local validation is establishing thresholds for student support based on the data. Using this metric, local teams can identify when to intervene and to what intensity. They can also create markers, for example, in the attendance risk factor to signal when to refine or discontinue an intervention.

O'Cummings & Therriault (2015) note that effective schools have learned to triage students and define student needs based on an EWS. In doing so, frontline educators validate the data of the tool and choose which data to act upon. The long-term vision is to establish rigorous progress monitoring using EWS tools for all students with interventions tied to the appropriate tier (Marken et al., 2020; O'Cummings & Therriault, 2015).

In many EWS, local analysis, context, and priorities determined the thresholds to which students would be given interventions. This means that academic, attendance, and behavioral support were given to students at different rates over time given the demands of the intervention, priorities, and local capacity of the system (Bruce et al., 2011). A student may not exhibit risk in all areas.

The locally defined threshold can identify the specific factors to target, for example, with students challenged by attendance, by creating a system of meaningful attendance incentives and mentoring to recognize student growth. This can be reinforced through selected Tier 2 academic supports which reinforce the student in the classroom through small group supports and foster a sense of belonging and ownership. This can ensure the tie of attendance to classroom behaviors with a target on academic success and a return of the student to universal support.

Data and methods

We collected data regarding the degree of implementation of the Montana EWS model using data from the Montana SLDS data warehouse, interviews, and surveys. Analysis of the SLDS data is focused on contextual, institutional, and student outcome variables found in the Montana SLDS and outline the 'demand' for the program.

The principal student outcome analyzed was graduation. The focus was on identifying the profiles of school level demand for the program by level of adoption. Data were analyzed in three ways. Continuous variables were analyzed with a General Linear Model. Graduation rate was the dependent variable, and the fixed factor was groups of schools defined by level of adoption. For categorical variables such as locale (a rural, town, city classification), a crosstabs feature was used (Pearson Chi Square) to gauge significance. Uploaded data were tracked. Schools are required to upload data to contribute to EWS results.

We explored the hypothesis that the presence of instructional and non-instructional staff would impact how a school accesses EWS results (linear regression). Through descriptive measures we frame the efficiency of the model aligning EWS predictions with eventual graduation status for all students that received an EWS probability between 2012 and 2020.

We also provide findings of a difference in differences analysis gauging the propensity in EWS schools of the EWS cohort to graduate versus all other students in the school (many schools only uploaded for a few students). This kind of analysis also distinguishes between high adoption EWS schools with low adoption EWS schools by comparing changes in graduation over time.

Fifteen districts were purposely chosen from among the 18 districts that expressed interest in the interview process (36 total participants). Purposeful sampling was used to gather data from a range of different districts with different upload counts, situations of economic disadvantage, indigeneity, and rurality.

The responses were open coded (inductive) that allowed certain patterns to emerge. Open coding focuses on the process of interrogating the data by asking questions relevant to emerging themes, verifying these themes across interviews, and organizing the emerging analytical framework based on the findings. This coding schema was confirmed with data on existing research literature, SLDS data, and the results of the survey (deductive).

The survey was sent to all schools who have participated in, or registered with, the Montana EWS system (154 contacts). Typically, this included the district superintendent, the school leader, and the school counselor.

The survey addresses the intensity of EWS implementations including providing data on the scope of interventions. It seeks data about interest in the EWS and how schools transition from data to intervention. The comparisons (Pearson Chi Square) allow us to focus on trends apparent between two categorical variables.

For example, we focused on whether the school was a pilot school (six or more years of implementation) when analyzing different data elements such as the frequency of intervention. This meant when we analyzed the frequency of intervention questions, we compared schools based on length in the program. The survey (22.73% response rate) was used to confirm the analysis of SLDS data and interview data.

Results

Users that reported a robust data culture in the school indicated that the Montana EWS worked well, and the process developed as intended. This sign indicates that there was a level of commitment once the value of the innovation was established. There became a clear tie of the data to intervention to outcome. The system as intended relies on this predictive analytic tool, its processes (the framework of the Montana EWS, data sharing, functionality of the web portal, and OPI support) and impact on graduation.

As revealed in the interviews there are a variety of mediating and moderating factors that determined the types of implementations and the variation in implementation within each type of school.

The primary factor seen in the data was the presence of a Multi-Tiered System of Support (MTSS) team or a team of educators working toward dropout prevention. Value, vision, dissemination, and the formation of a data culture are important factors. Survey data indicate the degree of spread of the data culture highlights the importance of informal and formal dissemination of the data working in tandem within intervention teams and faculty engaged in the actual work of the intervention, primarily mentoring.

The role of the Montana SLDS is important. Targeted professional development that focuses on medium and high adoption schools encouraged the depth of this spread.

One defining characteristic of this spread would be for teachers' use of the data that generates both formal and informal conversations. This level of faculty engagement relied on the vision of the school leader to implement dropout prevention strategies, the value found by all stakeholders in the EWS tool, and the reliability of the Montana EWS tool as shown by its ability to predict graduation.

Under the Hood

When data are uploaded by districts to the EWS, it indicates that the school is opting into the primary business requirement of the model—to provide local, real time, data about their students.

This local data supplements the Montana SLDS data that is used. One difference between the two is that SLDS data is both real time and periodic, based in data collections throughout the year. Local data is real time. Users typically follow a template; however, some Infinite Campus districts can load an Infinite Campus extract based on this template. In practice, there is a federated approach to supplying the local data to the Montana EWS.

The Montana EWS uses eleven logistic regression models that contain different combinations of variables depending on the significance they hold for each grade. The variables are selected out of 300 potential predictors used during the model refinement process with schools over the past decade.

Each model goes through a model refinement process each year where new additions are considered, and variables are removed that may no longer be significant to the calculation. This model refinement occurs in a separate process conducted in the R software environment which occurs with the data from the previous year.

Written into the stored procedure (SQL) is the coefficient for each model by grade and years in high school. The intercept is calculated based on the grade level coefficient multiplied by the median of the student's core data elements. The model building process involves fully saturated models that typically include the eighteen variables that have been determined to be the best predictors for dropout over time with one to two interactions between those variables.

Additional calculations are performed for each risk factor. Each factor is presented following the same protocol of subtracting 1.00 from the risk factors and multiplying it by 100.00 to calculate the odds ratios. The training process for the model generates fixed factors and dropout predictors. In the staging process, records are identified that focus on thresholds for at risk and extreme at risk according to the drop out probability. This is also completed for each risk factor, with, for example, grades at risk being assigned.

Model refinement occurs once a year. These core data elements are attendance rates, previous term F grades, previous term A grades, behavioral events in the last 120 days, suspensions over the last three years, repeater, credits per year, an on-track indicator assigned by the district, and absences in the last 60 and 90 day.

Models are refined by dropping variables that have the highest p-values one at a time. The Nagelkerke r^2 along with the C-statistic are calculated for the models with each change and compared to previous results to ensure the refined models have a higher likelihood of being accurate. The final models are then run using the training dataset and predicted results are compared against the actual results to determine the accuracy of each model.

Separate stored procedures are used for each of the three reports in the Montana EWS and in the calculation of state averages. The data from the EWS results table are used in each report and in the online interface available on GEMS for district users. For example, the student summary reports integrate data used to calculate the risk factors and dropout probability of each student. Data on the specific odds ratios during the last upload is also laid out by risk factor and dropout probability.

Data sharing

The system needs local data to work. Grades and discipline data, for example, are not directly collected at the OPI. When it came to administrative tasks involving the use of the Montana EWS, the survey data reveals that most people that uploaded were not leadership or counselors. Often this involved an attendance secretary, technology professional, or the school librarian. This signals that the person uploading may not have experience with the benefits of the EWS or see the position of the data in their school community. This may have impacted buy-in for the process and evaluation. Many users with hands on experience did not have access to the SLDS web portal. Conversely, many people who had access to the SLDS web portal were not involved with policy or school level interventions.

Schools interviewed suggested they typically upload at least quarterly. This variation is noted in the data. Evidence indicates that schools that first started participating after 2015 upload less frequently than those that started earlier. Survey respondents reported that data was uploaded on average for fewer students in the school than the school population.

Most frequently, users uploaded data for 100 to 500 students. This is in line with the finding that EWS schools are most frequently under 500 students (in communities which are mid-size relative to Montana) or in many schools only a portion of their student population was added to the Montana EWS. Comments from schools that shared data were minimal (4) and focused on the ease of the system to upload data.

One counselor remarked that it was not difficult at all, and she just needed to review a tutorial. A principal placed this in context: "I think it's really user friendly. I understand the issue with OPI and all the different student information systems in the state. Whether it's Power School or Infinite Campus. It's hard to get one size that fits all."

Staffing did not appear to be related to the number of times data was uploaded. To explore the hypothesis that the presence of faculty and certain non-instructional staff is related to the incidence in which a school has shared data with the EWS, we used five different regression models to see how much, for example, is the incidence of upload explained by the pupil teacher ratio. We found that pupil teachers ratios have a moderate association with upload frequency ($r^2 = 0.230$).

The higher the per pupil ratio the more likely a school would upload more frequently. This is contrary to what we expected in that lower pupil teacher ratios would indicate that the teacher had more time to focus on individual students when compared with schools with similar characteristics.

We also looked at counselor ratios, psychologist ratios, social worker ratios, and librarian ratios and found that they explained little of the variation in average uploads per year. High adoption models, according to our respondents, originated from the school leader and are dependent on how vision and value of the innovation were communicated to faculty and support staff.

OPI support was seen as a catalyst among high adoption schools. Relationship building was a common theme across the interview and survey datasets.

One principal remarked how he was involved in the design process of the OPI Early Warning System in 2012. As a result, he presented with SLDS analysts on the benefits of using the OPI system and highlighted the EWS inspired mentoring programs in his school. He also frequently talked about the Montana EWS with groups in local associations (School Administrators of Montana).

His takeaway from this experience is that success depends on the quality of relationships established with students, teachers, school leadership, and the OPI. Some respondents praised the work of SLDS staff in designing and supporting the district's EWS program. Two respondents remarked that no matter what the issue, they feel that their voice was heard. This support included the revisions of the tool during the pilot phase, extensive outreach at conferences about the tool, and one on one support from SLDS staff about integration of the diagnostic tool in their schools.

Three users wish the SLDS would provide additional support including more presentations at conferences or to groups such as the Montana Federation of Public Employees.

Perspectives on the online platform

Opinions on the design of the EWS focus on the similarity to MAPS reporting, which was seen as a benefit since teachers were familiar with the format. Users commented on the summary report and the detailed report.

One principal distinguishes between the summary report (where he 'lives and dies' with data distributed to the faculty) and the individualized detailed report (which is good for a focused meeting about an individual student, for example, with parent meetings). Users commented on the overall transformation with SLDS modernization. Users were pleased with the ease of access to data elements on the SLDS and commented about the professionalism of the Power Bi dashboards.

Criticisms of the online tool show areas for improvement of the Montana EWS. This view under the hood also illuminates general issues with an EWS that could benefit other state models. Accessing the portal is the most cited difficulty that users experience with the EWS. This criticism is common for all OPI applications and reflects enhanced security protocols. An Assistant Principal remarks the process of logging into the EWS is difficult: "I don't even try that day to have a meeting that day because I'm going to get an error that doesn't allow me in. So really, you must plan to pull the data."

A user remarked that the decision to switch to a vendor model was that the EWS had insufficient longitudinal analysis. A school counselor expands on this point by saying "You must prepare how you are going to organize the data. You must reorganize it the same way each time (to create our own tracking system)."

And this process of preparation reportedly takes time especially when schools try to disseminate their own data based on EWS data that integrate additional data points. These points include longitudinal data from the EWS, achievement data (ACT, MAPS, Smarter Balanced) and qualitative data from teachers. All this reflected time spent improving dissemination and fostering a connection with the school intervention team.

Quality of the EWS

Overall, user reports about the quality of the EWS were positive and showed encouraging signs of the development of a data culture surrounding dropout prevention. Even the schools that did not participate in the EWS remarked on the benefits of an early warning system.

A principal noted the time focused on EWS data has been a routine of her school's data culture: "I think EWS just keeps it in the forefront. If we didn't have a system in place, we would forget. But now, it's always in the forefront. Teachers have got used to receiving the data. I think, it just allows us to keep the students in the forefront."

Establishing the EWS as part of a set routine, often part of a MTSS process, allowed users the opportunity to focus less on identifying students and more on placing time and resources on the actual supports for student success. This was seen as a catalyst for a data culture surrounding student engagement and graduation.

There were many remarks about the reliability of the data. A principal was positive about the consistency of the data: “Everything is consistent and easy to see.” Another principal remarks that this consistency and objectivity makes EWS data more relevant than feedback from teachers or counselors. This is because trends in this data across multiple times that data is pulled enables the work of the dropout prevention team.

Interviews highlight the ability of these teams to use longitudinal data to target resources to those areas most in need and that would likely have the largest impact.

One principal remarked at how easy the data is to share with fellow administrators, faculty, and parents. Administrators further comment on the ability to share data in an objective fashion that focuses on attendance, behavior, and grades. Often this process was done by paper handouts and spreadsheets that administrators and counselors disseminated.

One principal discusses the most beneficial aspect of the EWS in the context of the reliance on the tool: “I think without the EWS data we would beat our heads against the wall trying to figure out and identify a lot of those students. We don’t have the time or resources to do what the EWS does. You know it is quick and easy in terms of time and resources. I imagine all the time I’d spend trying to compile all that data. The per student cost is minimal compared to what it would cost without an EWS.”

Of the risk factors, users generally trusted the data and they found the data displays adequate. However, mobility was mentioned by multiple users as misleading. Users remarked that EWS is piecemeal especially in the context of the mobility piece that may identify students who would otherwise receive universal support into a tiered intervention. They were confused of the weight mobility factored into the overall calculation of dropout probability.

Mobility is seen by multiple users as raising ‘false alarms’ that can only be resolved by monitoring students over time. Requests were made for FAQs which focused on mobility, how it is calculated and what impact it has on dropout probability.

Tying Processes to Outcomes

At the school level, reforms that coincided with the use of the Montana EWS included the priorities to address dropout prevention, the efficiencies caused by using the tool, and the communication strategies used to implement a whole school reform.

These priorities were described in the interviews and the surveys as originating from a school leader that encouraged frequent use. Indeed, frequency of use is important at the school level (frequently retrieving data to monitor students) and frequency of engagement with students as seen in early identification and progress monitoring.

Communication is a key indicator of the degree of institutionalization of the EWS and dropout prevention. Often, this is the degree that the data was seen by counselors, teachers, and parents and actively used to make decisions.

A school leader describes that communication is key to the process of assigning interventions. When designing early interventions, he describes how he talks to staff to get perspectives on each student’s circumstances then looks at the data and verify with staff as to the data’s accuracy. He engages the families in the process, something frequently done with the support of EWS data.

Building relationships is important for him, for example, when finding a student, a mentor who is the right fit and defining which resources are available for each student. The goal is to increase student engagement by finding meaningful data informed supports.

Approximately forty percent of schools that had registered with the system are high adopters of reforms that were inspired using the Montana EWS. Follow up in these schools was frequently data informed.

The intensity of student support in low adoption schools was at times defined by universal interventions and the support that can be provided by a teacher in a classroom providing core instruction. High adoption schools tend to intervene at a greater depth than other kinds of adopters. The interventions include small group tutoring tasks or more intense one on one supports. The depth of these interventions is dependent on demand, capacity, and priorities.

Many schools do not have the need to focus on dropout except in an informal capacity (non-adopters). However, adopters shared certain school characteristics, such as economic disadvantage, although there are important differences between low and high adopters in terms of the impact on graduation.

The efficiency and effectiveness of the Montana EWS system can be identified by comparing the calculated dropout probability with the principal outcome, graduation rates for the same group of students (4-year cohort graduation rates). This provides data on how efficient the model is in predicting dropout.

As we can see in Table 1, students that are extreme at risk (40% dropout probability) graduate at rates much lower than at risk (15 % dropout probability) and non-identified population (less than 15% dropout probability). The counts of students that received a dropout probability and the eventual graduation numbers indicate that the model predictions generally align with the dropout probabilities assigned.

Table 1

Comparison of EWS Dropout Predictions to Actual Dropout Rates

	Number of students	Average EWS dropout prediction (p)	Implied EWS graduation probability (1-p)	Actual graduation rate
Students ever scored at extreme risk of dropping out	5,838	35.6%	64.4%	62.6%
Students ever scored at risk of dropping out, but never at extreme risk	5,068	9.8%	90.2%	90.1%
Students never flagged as at risk of dropping out	18,507	1.9%	98.1%	97.0%

Notes: Actual graduation rate is defined as 4-year graduation rate based on 9th grade cohorts from AY 2009-2010 to AY 2017-2018. Sample is restricted to students ever loaded into EWS.

In the context of effectiveness this trend may be a cause for concern. Successful dropout predictions models could show a difference between dropout probability and eventual graduation since identified students were exposed to interventions designed to avert dropout. The non identified students also had a graduation rate that was lower than suggested by the dropout probability. This indicates that some students were not identified and eventually dropout out (false negative).

These trends suggest that there was a varied implementation of the program where many students in low adoption schools did not receive as extensive interventions as in high adoption schools. Thus, this would not represent a treatment effect since low adoption schools are included and their inclusion does not accurately measure the full impact of the reform.

The effects of the EWS on different populations of students within the same school indicate that those students with an assigned EWS dropout probability had graduation rates that were 3.6% higher than students in the same school who were not loaded. When comparing schools that uploaded data at least twice/year (high adoption) with low adoption schools, students in high adoption schools were 0.4 percent less likely to drop out and instead stayed in school. This dropout probability is relative to students in the same school in years when the EWS was not used.

Stakeholder Recommendations

Longitudinal data was seen as crucial to identifying interventions, modifying interventions once in place, and creating thresholds for students to discontinue support.

The principal recommendation among users was to create ways to manage longitudinal data with reporting based on each risk factor and dropout probability. Ideally, this would contain data from participating elementary, middle, and high schools. Longitudinal data is needed for progress monitoring. Respondents also request professional development on how to use the tool for progress monitoring and identify what are triggering events involved in the process. This process should focus on the work of student advocates, mentors, and teachers, specifically how EWS data can be used for evaluation of individual student needs.

OPI outreach and professional development

Interview respondents discuss how the outreach by OPI was of good quality. They commented on the need for more presentations and workshops about the EWS. Respondents from high adoption schools discussed how they wanted to focus less on the use and requirements of the tool and more on the process of identifying students at risk, establishing thresholds for support, and processes for progress monitoring of students.

Even schools that are no longer using the Montana EWS request this support (integrating data into intervention planning). This reinforces the finding that the lessons learned from the Montana EWS model, in particular the support OPI provides to schools, applies to all schools no matter which EWS they use. EWS data is valued in other regards. Many educators also found that using the EWS data for other reasons besides dropout prevention was beneficial, such as the evaluation of MTSS procedures and for grant writing.

Interventions

One finding from this study is that many schools are in the process of developing a data culture surrounding the MTSS process. In professional development activities, they claimed that OPI should create a clear tie between the EWS and MTSS intervention strategies. Specific support could focus on reinforcing local thresholds for triggering and monitoring an intervention.

Access and business requirements

The most frequently discussed obstacles occurred in the context of logging in. This issue was seen as more important than issues with upload. Respondents desired a single login for all OPI applications that did not expire every three months. This is a common criticism of some OPI applications. Users also remarked on the process of gaining access to the web portal. A streamlined process of accessing, managing, and sharing data is needed.

Risk factors

Many users commented about mobility and how it increases incidence of 'false alarm.' OPI should clearly define for end users why mobility is in with the model and what is the contribution of mobility to the model (FAQ).

Discussion and Conclusions

School officials in Montana reported many positive features of the state's Early Warning System. The Montana EWS is free of charge and available for all schools. Research literature has identified that through much of their infancy, EWS were the purview of large school districts.

Today, the primary source of EWS data is from private vendors. By offering the opportunity to access an evidence-based system that is designed for a range of district sizes and is cost-free for districts, the EWS programs provided accessibility and coverage. Moreover, the Montana EWS focused on professional development for end users, something that is often missing from vendor models. According to respondents, the system is highly accurate, OPI outreach and support is comprehensive, and costs of the model are minimal even when factoring in staff time.

While making the interventions more efficient, there was a decline in support necessary per student due to early identification. This generates cost-savings that can be used to provide support for other at-risk students or to support other programs in the school.

An additional benefit of the EWS data is the ability to predict behavior in a way that is not dependent on demographic variables, economic disadvantage, and student status (e.g., disability or ELL status). The only demographic data that is used in the Montana EWS to calculate dropout probability is birth year. Indeed, this focus on those variables that are more under an educator's control removes potential barriers to intervention and biases. Scale is crucial to understanding the degree of implementation.

The process of scaling up the program met many successes and challenges. SLDS data indicated that the motivations (economic disadvantage, locale, and student demographics, graduation rates, attendance, and achievement) were similar between high adopters and low adopters suggesting that the demand for the Montana EWS, or any EWS, is similar.

The Montana EWS has a track record of twelve years of serving Montana's schools. Its model is unique. This state program has an opt in model whose schools shared many of the same endogenous factors. These factors highlight areas in which the experience of the Montana EWS does contribute to the research and policy literature about the use of EWS in schools.

This article has focused on the mechanics of the EWS, what users experience, and factors that showed the success of the model. We have not tried to 'sell' the Montana EWS model, rather show what is under the hood so that we can make comparisons between what the Montana EWS experienced and best practices in the field. Unfortunately, models for EWS best practices are only emerging. Most focus on district level implementation and do not focus on state or vendor models.

What we have seen here is that the Montana EWS has a proven track record and does show different positive and negative attributes. Both can be used to highlight ways to improve the implementation of Early Warning Systems.

Findings from this study can be used to inform educators about the use of the tool. Respondents to the interviews noted many reasons why schools would switch to EWS models provided by Infinite Campus or Power School (the two main student information systems in Montana). These vendor models provide integrated access to the student information system.

Vendor models do not require additional upload of data. Users cited the main benefit of the Montana EWS was access to a predictive analytic tool with longitudinal school level results and the professional development by the SLDS in the use of the Montana EWS or any EWS model.

What these systems miss is access and coverage for all schools. Montana EWS has a mosaic of users with different student information systems and different priorities for using an EWS. What they share is a demand for the tool evidenced by similar school factors. There are important differences shown by institutional variables and student outcomes measures between adopters and non-adopters.

The Montana EWS model is fully adopted among schools with high implementation. One of the reasons why this is occurring is that local priorities dominate the decision to access and make use of the data. Local conditions are important. The similarity between high adopters and low adopters stresses the point that it is the larger school environment that set the course for interest in the EWS model. Combined with this are the differences between this group and non-adopters.

Non-adopters may have not seen this need for this tool given that their environmental factors are different and school size is predominantly among schools with less than 150 students. These small schools may not have seen this need for the tool since relationships between students and faculty or administrators may be stronger due to the intimacy of the educational setting.

High adoption was most common among those adopting between 2012 – 2017. These schools engaged in a system wide reform, something which distinguished them from low adoption schools. Time with the EWS program was seen as crucial to normalize practices surrounding dropout and the benefits of the tool.

The Montana SLDS should measure its success over the long term, through involving a variety of stakeholders, and developing a data culture at the state level surrounding dropout. The degree of OPI outreach and individualized support was important. As with many aspects of Montana education, there is local control and decision making.

The degree of EWS implementation in Montana 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 to school programs was seen as a catalyst to school level change in high adoption schools.

School and district officials made several recommendations, including the need for more ways to manage longitudinal data and the desire for more support in how to integrate the risk assessments with specific interventions. Overall, the responses imply that the Montana SLDS should measure its success over the long term, through involving a variety of stake-holders, and developing a data culture at the state level surrounding dropout prevention.

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