Discover Education

Case Study

The tie of data to intervention: a case study of the Montana early warning system

Robin Clausen[1]

Received: 15 November 2023 / Accepted: 4 February 2025
Published online: 17 February 2025

Abstract
Early Warning Systems (EWS) are research-based analytics that use statistical models to assess dropout risk. School leaders use this analytic to consolidate data about a student and provide actionable data to craft an intervention. Little is currently known about the processes involved in school implementation or data use. By analyzing Montana EWS data from the past 10 years to see if it is effectively used in interventions whose outcomes demonstrate a linkage back to the data, this case study addresses this data use (the first step in the logic model of intervention).

Keywords Predictive analytics · Data use · School policy · Early warning system · Dropout

1 Introduction

Early Warning Systems (EWS) are predictive analytic tools that have been used in dropout prevention for the past two decades. These systems contain data on a student's risk factors and the overall probability that they will drop out. Often paired with professional development offered by a local education agency or state education agency (SEA), these systems focus on making results useful for educators. They provide objective indicators to frame risk-based analytics, which have been trained against prior year(s) data. They are often used in conjunction with other inputs, including feedback from parents and teachers, or a student-signed behavior contract. The degree of communication of EWS data among educators and the feedback loop to improve this data are under investigation in this study. These traits can show a linkage between data, the intervention, and an outcome. Often this is accomplished within the context of Multi-Tiered System of Supports (MTSS) interventions, which allocate interventions according to student need, the local capacity to support an intervention, and the priority given to making an intervention happen within each context.

EWS reached their tipping point in 2012, when many large school districts experimented with the dropout prevention tool and a number of states began to incorporate EWS data into their accountability systems through their statewide longitudinal data systems (SLDS) [1]. The Montana EWS, which began its pilot phase in 2012 and is a unit of the Montana Office of Public Instruction (MT OPI), is based on an opt-in model, where Montana schools have universal access to the tool, though only a portion choose to use it. Since then, EWS tools have also been offered by Student Information Systems in Montana, most notably Infinite Campus and Power School.

The Montana EWS has demonstrated that it is possible to identify students that are in danger of dropping out by using established individual and school-level indicators that can give warning to the signs of potential dropout [2–6]. By focusing on attendance, behavior, mobility, and academics, the Montana EWS identifies intervention thresholds in a manner that is independent of demographics, indicators of economic disadvantage, or factors that may be out of a

✉ Robin Clausen, robin.clausen@mt.gov | [1]Montana Office of Public Instruction, PO Box 803, Big Timber, MT 59011, USA.

student's control (e.g., foster care or disability). This is displayed to the user as a dropout probability and includes metrics for related risk factors. Schools receive this data as a summary for the school and detailed reports for each student. The policy decisions regarding how to identify students, frame thresholds of interventions, and use data to monitor students reflect local choices and control. The Montana EWS does provide guidance as to these processes.

EWS models often demonstrate a strong association between the dropout probability based on certain risk factors and any eventual dropout status. However, the Montana EWS faced a challenge when identifying students: Students that are identified as dropout may have received extensive support from the school community and graduated instead. A desire to understand these false positives inspired this research, which opens the door to inquiries about the effectiveness of the system in Montana. The first step is to analyze data use to gain insight on when, how, and to what degree schools use data to engage in interventions.

Research is not settled as to the data use, nor its role in the logic model of most EWS. Data use in this context is the degree that evidence-based EWS results are used by educators to craft interventions. EWS data may then move the needle and inspire action: schools intervene with students and indicators show improvement in student outcomes, such as increased graduation rates [7]. Research on data use of EWS systems is sparse, and little is known about the Montana or SLDS early-warning systems [2, 7]. This is perhaps due to both difficulty with describing the casual linkage in this context and answering the pivotal question: Do they even use the data?

EWS data use in small schools is a case in point. Educators from small schools that use the Montana EWS tool claim that they may know who their at-risk students are, but they may not know how to operationalize the data to make a successful intervention over time. We see this in particular in Montana, where small schools are many and educators frequently already know their students and parents; they're often neighbors. While some stakeholders in small schools still find value in the tool and use EWS data to know which interventions to choose, in what context to apply them, and how to adjust those interventions over time, others do not find this value and report that there is less of a demand in small schools due to size. Understanding this difference involves framing the demand for EWS interventions, the vision and value found in the data, the communication strategies involved, and each school's priorities regarding EWS-inspired interventions.

2 Research questions

Focusing on an established model that has been serving Montana's students and schools for over 10 years, this study investigates the data culture surrounding use of the EWS tool and the pivotal role of interventions in the process. By investigating trends in EWS development, especially in the years before the pandemic, we are better able to understand how participating schools have implemented data-driven dropout-prevention strategies, and if there are signs of a renewed focus following the pandemic on dropout prevention among schools classified as "high adopting."

In particular, the study investigates the process of tying data to an intervention and how this process may be impacted by policy choices through the following questions:

- To what degree are Montana EWS data incorporated in school decision-making?
- Do schools that use the Montana EWS have different characteristics and student outcomes than schools that do not?
- What policy changes occur in schools that have used EWS in their intervention model?

In this analysis, Montana schools are classified according to level of adoption: high adopters, low adopters, and non-adopters. Many similarities are apparent between high and low adopters, such as per-pupil ratios and per-pupil expenditures. Nonetheless, some schools were motivated to engage this dropout prevention tool and others chose to experiment or leave it behind. High adopters tended to value their teachers more as evidenced by teachers that stayed in the same school for many years. They also tended to have more economic disadvantage than low adopters and non-adoption communities. Many respondents from low-adoption schools claimed they did not use data in their intervention decisions and 38 percent didn't intervene at all. High-adoption schools' use of the tool depended on the vision and values of the school leaders and the communication/dissemination strategies involved. An analysis of non-adopters indicated dropout is less prevalent, attendance rates are stronger, and achievement data is higher when compared to adopters. In many of these schools, there wasn't a recognized demand for dropout prevention and, even when it was recognized, there was the perception that many schools were too small to warrant use of the tool.

3 Background

3.1 Data use

The scope and processes of an intervention are determined at the school level and reflect policy choices. For example, a school's decision to address academics through an MTSS process is a policy choice; MTSS is often linked to behavior, but not to attendance and academics. Data use is also a policy choice: Schools determine the degree to which they align use of the EWS data with their data culture. The causal chain is that staff's use of the data to craft an intervention—and the intervention itself—leads to a certain outcome. A necessary link in this chain is the choice to use the data and adjust its use over time. As a result, either a narrow or broad application of the EWS tool is implemented by school leaders.

EWS data use with a broad application is characterized by impact on the development of a data culture, early identification, and progress monitoring. These steps address how the Montana EWS model helped put students first in dropout prevention by diagnosing risk and making student data available to each school. The data-use process in Montana addresses the following themes at each step of an intervention cycle. Early identification is the primary goal of the EWS system, providing both the warrant and the main strategy. Data culture, in part, defines how frequently users identify risk and return to the tool while adjusting an intervention. Finally, effective monitoring of an intervention once in place is enabled by progress monitoring, which determines the continuation or end of an evidence-based intervention.

Policy choices guide interventions; early identification alone does not. A step must be taken by the school to take EWS data and frame it within strategies for dropout prevention over time (data use). This addresses vision, value, dissemination of EWS data, and communication—processes that inspire data use and are inherently linked. The vision of the school leader could be a determining factor to the intervention, more so even than that of the district superintendent or guidance counselor, as seen in the case of Montana. School leaders can help others find value in the EWS innovation, making use of the data by intervening with students most at risk. This involves communication and dissemination of the EWS data, a pivotal point during which data use can lead to an intervention. Interventions and follow-ups reveal the nature of the data culture surrounding dropout prevention. Indeed, progress monitoring shows how embedded dropout-prevention strategies are in the school, demonstrating repeated use over time and the adjustment of intervention strategies.

3.2 Montana EWS

MT OPI's outreach involved developing and refining the diagnostic tool and engaging in professional development on best practices to use it. In this context, outreach focused on navigating the online platform, managing and uploading data, interpreting the results, and bringing those results to an MTSS committee. The EWS program pursued four overarching goals:

1. Create and maintain a statistical model that accurately predicts the odds of a student dropping out (model development by MT OPI).
2. Identify at-risk students before they drop out (professional development to schools provided by the MT OPI).
3. Help schools identify factors that are impacting each student's dropout risk to prioritize and target interventions (professional development provided by the MT OPI).
4. Help schools understand dropout risk trends at the school level to make decisions regarding policy and programming that may influence dropout risk (professional development, for example, through the work of a Montana EWS Data Coach).

These strategies all focus on data use. Professional development included assistance by the Montana SLDS to schools in the management of data and data coaching as to the use of the data. The diagnostic tool creates profiles for schools and students. Once users log into the system, they are presented with four choices, two of which focus on student-level data. Access is typically limited to the school leader and the person who managed the local data in the system. The profile-creation process includes uploading data that is needed to run the Montana EWS that the SEA did not routinely collect (e.g., grades and discipline data). In most cases, EWS data is then compiled and disseminated by school leaders, often through spreadsheets or handouts.

The principal element of the diagnostic tool is the user interface that is populated with results of the logistic regression modeling by student and grade level. In Montana, this interface is available in the SEA statewide longitudinal data system (https://gems.opi.mt.gov). Common EWS warning signs include missing 20 days or being absent 10 percent of the school days; two or more behavior infractions; and inability to read at grade level, low GPA, or two or more failing grades in courses in the previous year [8]. Achievement data is not commonly used in these systems because grades are seen as a stronger indicator in reflecting performance over time. According to interview respondents, by focusing attention on a small set of evidence-based indicators, users can conserve time and resources when managing and communicating the Montana EWS data. By keeping it simple, it's easier to define objective, evidence-based relationships and prioritize interventions.

The MT OPI did play a supporting role, both by providing the development framework and offering professional development for school users to foster interest and engagement with the tool for those schools that opted in. Once the system was in place in 2015 and business rules governed the refinement and training of the data each year, the onus of Montana EWS was on professional development. This professional development was supported by data stewards at the SEA and individuals who worked in participating schools, such as dedicated SEA data coaches.

4 Data and methods

4.1 SLDS data

To investigate if and how Montana EWS data is used to craft interventions, we collected data regarding the degree of implementation of the EWS model using SLDS data, interviews, and surveys. SLDS analysis focused on administrative and student-outcome variables found in the Montana SLDS. The focus was on identifying the profiles of demand for the program by level of adoption. We used data from all schools in Montana to analyze three categories based on upload counts: high adopters, low adopters, and non-adopters. The benefit of the comparison to low adopters and non-adopters is that we can estimate what happens in the absence of the Montana EWS model due to common school level characteristics such as economic disadvantage and locale. Moreover, we can assess the demand for the EWS tool by comparing student outcomes on each of these three levels.

Schools must upload eight data elements (e.g., grades, satisfactory progress flags, and discipline data) to the Montana EWS to generate EWS dropout probabilities and data on risk factors. The more often a school uploads data, the more likely they are accessing and using the data. The measurement differentiating adopters versus non-adopters is at least one upload in any given year. The difference between low and high adopters is that high adopters access data at least quarterly.

We categorized schools by adoption status based on upload count; dissemination patterns, as seen in the interviews and surveys; and data use factors (e.g., vision and values), as found in the interview and survey data. We cross walked upload frequency with the qualitative findings of schools with the same upload frequency and provided evidence on dissemination patterns. It is assumed that these groups differ based on interest in the model, demand to address dropout prevention, vision to implement and use the tool, value placed on identifying and acting on the needs of at-risk youth, and dissemination practices in which all actors, including counselors and teachers, have access to EWS data. Once the initial categorization was made on upload count, we aligned SLDS data (91 schools in 2019) with interview data (15 schools) to gauge which level of adoption identified through the interviews coincided with upload count. Next, we aligned these groups with the results of the surveys (36 schools). This process focused on areas of overlap and those where characteristics can be broadly assigned to each level of adoption.

Upon first upload, schools established an EWS profile, which demonstrated interest shown, initiated patterns of adoption that could be assessed, and allowed us to distinguish between low and high adopters. We further distinguished between kinds of high adopters based on how progress monitoring was used, and whether the school reported frequent engagements with the data for their at-risk students.

SLDS data was analyzed using a crosstab feature with Chi Square analyses (categorical data), a general linear model for comparison between groups with a continuous dependent variable, and a linear regression model for comparison between continuous dependent and independent variables. The Chi Square test compares observed results with expected results, with the goal of assessing whether any differences between observed and expected results occur by chance. A *p*-value of 0.05 is used to assess whether any differences occurred by chance or not.

The general linear model was used as a first step to identify possible causation. A student outcome is the dependent variable, and the fixed factors were classified according to the level of adoption. Linear regression is used to predict the value of a variable based on the value of another continuous variable (the degree that the variance is explained). Linear regression is used in two ways. First, it focuses on the upload count as a consequence of a change in contextual variables (e.g., teacher tenure and salary). The upload count was regressed by these teacher-level variables and selected student outcomes, with the goal of understanding whether schools with teachers with longer tenure or who were appropriately valued for their work led to more intense engagement with the EWS data. Analysis focused on variation in a student outcome in the same year that the EWS innovation was adopted. Secondly, linear regressions were used to explain the degree to which upload count is predictable by variation in pupil/teacher ratios, counselor ratios, librarian ratios, and social-worker ratios. The goal is to see if schools made use of the data more frequently when these ratios were lower (they had more staff capacity to address dropout prevention).

4.2 Interviews

Interview data was collected in November of 2022. The interviews focused on EWS level of adoption and processes and policies at the school level. Fifteen schools were purposely sampled from a pool of 18 schools that expressed interest. Schools were selected based on socio-economic criteria, size, and high proportions of Native students. We coded interview transcripts via an inductive process. Inductive coding represents a ground-up approach to derive codes from the data. Coded responses allow certain patterns to emerge. This process involves line-by-line analysis of the data, interpretation of the data by the analyst, and grounding of the emerging coding schema in the data at hand. The grounding process was enabled by open coding. Open coding is the process of systematically 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. Themes are then constructed from the emergent coding framework before a deductive last stage integrates survey and SLDS data.

4.3 Surveys

The survey addresses the intensity of EWS implementations, including providing data on the scope of interventions. It seeks data about schools' interest in the EWS, their use of it, and their implementation of interventions based on the data it provides. Survey data was used to confirm the findings of the SLDS data (school demand) and interview data (vision, value, dissemination, and communication). The secondary role of the survey data was due to sample size. We achieved a 23.38 percent response rate from a population of 154 principals and guidance counselors (primary users of the Montana EWS). The sampling process was purposeful between groups (types of districts/schools). Chi square analyses (categorical data) focused on years of implementation (six or more/five or less years), size of the district (less than 450/greater than 450 students), and number of individuals using the EWS data by district (five or more/four or less individuals). When asked during the interviews how many people had direct access to the EWS data, respondents reported on average four individuals per school. Often, other individuals had access to summarized data. Invitations for the interview and survey were sent to all staff that have access to their district's SLDS portal. Teachers generally do not have access to the portal. Principals and guidance counselors have access and distribute data to teachers through a variety of modalities, including spreadsheets and handouts.

5 Results

5.1 To what degree are Montana EWS data incorporated in school decision-making?

5.1.1 Summary table

*Usefulness of the tool spurred high adoption. This coupled with systemic reform surrounding dropout prevention
*Many low adoption schools disengaged from the tool or used EWS data solely as a reference
*38% of respondents reported that they do not use dropout prevention data in their decision making about interventions and intervene less than 50% of the time

In schools that use the tool fully (high adoption), interview respondents agree that the utility of the EWS tool inspires interventions (they intervene more frequently than in the past). Low-adoption schools expressed interest in the model but did not implement it. There are questions as to whether these schools had policies that prioritized dropout prevention in the first place. Of the survey respondents, 48.28 percent reported infrequently using EWS data—or any dropout prevention data—to plan and implement interventions (this included both high and low adopters). Some of these high adoption schools did not use EWS data when intervening with a student but did use EWS data as a tracking tool.

Schools that had dropout prevention strategies in place, such as regular use of an EWS, engaged in interventions more frequently. Contextually, this occurred when teacher attributes like tenure and salary were much higher, but socio-economic indicators suggest that the high-adoption schools were more impoverished. Also, schools relied on factors that were more under the control of educators including a strong leadership vision, clear communication strategies, and an involvement of a variety of actors, including teachers, in their dropout prevention programs.

Of the schools interviewed, about half reported the EWS-identified students received EWS-based support "often" or "always." Among these high-adoption schools, there was intensive engagement as claimed in the interviews. Among all adopters, there were other indications of the depth of data culture. While 79.3 percent of EWS-inspired interventions received a follow up, the extent to which this follow-up was informed by EWS data varied between high adopters. Some users implemented a regimen of progress monitoring (where data was checked multiple times across the course of intervention(s)); other school teams followed up and ended an intervention.

Approximately two thirds of the EWS schools were classified as low adoption, as demonstrated by the linkage of qualitative data with usage data. Data on low adoption provides an important comparison since adopters share many characteristics of the demand for an EWS and many of the same environmental conditions. This allows us to ask what would occur when EWS data is not frequently used compared to those schools facing the same conditions that do frequently use the data. Data was reportedly not part of the intervention process in these schools, as seen in interviews of low-adoption schools. This indicates that many schools explored the EWS system but did not use the EWS data in intervention strategies. Often, analysis of the data was completed by the school leader, who may have acted on the data independent of an MTSS committee or used the data solely for tracking purposes. In these cases, counselors and teachers may not have been involved. The person tasked with managing the data was often the attendance secretary or a member of IT support staff, someone typically not involved in designing interventions.

Another insight of the intervention data is that 38 percent of educators report that their school provides interventions less than 50 percent of the time. This means that, for a variety of reasons, respondents indicate that their low-adoption schools provide interventions less frequently than in other schools; in fact, these schools take advantage of fewer than 50 percent of the opportunities to intervene with a student.

The outcome data of the EWS system (2023) provides systemwide trends. Of the EWS students, 80.37 percent were identified as future graduates and did, indeed, go on to graduate; 8.46 percent were identified as dropouts and did go on to dropout; 5.16 percent were identified as graduates, but instead dropped out; and 6 percent were identified as dropouts and instead eventually graduated. While this 6 percent may be a sign of a potential inaccuracy within the Montana EWS system, it is, regardless, a success for the students involved and an indicator that they may have received research-based interventions to help them graduate.

Overall, schools used the EWS model at different intensity. Many EWS schools did not use the data when crafting an intervention and reported that they indeed intervene with EWS students infrequently, less than 50% of the time. Nonetheless, most users did use the tool in dropout prevention decision making and many schools reported that they intervened with students at a high level of intensity. This success was seen more frequently than in the past as evidenced by the increasing counts of false positives (students that were identified as dropouts, but in turn graduated).

5.2 Do schools that use the Montana EWS have different characteristics and student outcomes than schools that do not?

5.2.1 Summary table

*High adoption school communities are more impoverished

*High adoption and low adoption schools have a similar demand for the use of the tool as evidenced by similar attendance rates, graduation rates, and ACT composite averages

*Rural schools may have less of a defined demand for the tool. Many of the schools are in intimate settings and there is a perception that stakeholders do not need a tool that aggregates student data

How data may be used is based on EWS demand in Montana (measured for fiscal year 2019). Analyzing data from high adopters, low adopters, and non-adopters allows for the comparison of related outcomes. Outcome measures between high adopters and low adopters were similar, but high adopters tended to be situated in more rural, disadvantaged communities. The difference between adopters and non-adopters indicated that there may not have been demand for the tool in most rural communities as seen in Table 1.

There is a similar profile between all kinds of adopters and non-adopters. A school's demand for the EWS can be seen through various indicators, outcome and institutional among them. An understanding of this demand may inform state policymakers about the likelihood of scaling the EWS program. The composition of the school community based on locale is statistically significant ($p < 0.001$). In high adoption schools, equal percentages of schools are in towns (45.56 percent) and rural areas (45.56 percent), while the town (21.71 percent) and rural (63.57%) rates from low-adoption schools vary significantly. When comparing low-adoption and high-adoption schools, low adoption occurs more frequently in rural areas as a proportion of the total number of low adoption schools.

Table 1 Locale, economic disadvantage, and student outcomes

	High adoption	Low Adoption	Non- Adoption	F	Significance
Locale (Schools)					
City	8	19	38	NA	NA
Town	41	28	64		
Rural	41	82	486		
Economic Disadvantage					
SIDE Estimates*	247.96	257.50	272.81	6.492	0.002
Student Outcomes					
Cohort Graduation Rates	86.24%	86.50%	93.21%	7.915	0.001
Satisfactory Attendance Rate	40.16%	40.39%	49.24%	19.018	0.000
English language assessment (percent Proficient)	44.43%	42.88%	50.71%	6.360	0.002
ACT Composite	18.72	18.54	19.54	4.029	0.020

*SIDE is a National Center for Education Statistics estimate of the responses based on the American Community Survey (ACS) that have a geolocated income to poverty ratio. For a community, ratios of 100 signify that every ACS neighboring response is at the poverty level

There is a clear correlation between the frequency of dropout-prevention tools' usage in schools (and, by extension, interest in addressing issues of dropout) and how economically disadvantaged their students are. A measure of economic disadvantage is based on data from the American Community Survey (ACS—https://www.census.gov/programs-surveys/acs). School-level poverty measures sponsored by the Institute of Education Sciences are based on a geolocated address. The Spatially Interpolated Demographic Estimates (SIDE) for these schools were statistically significant ($p = 0.002$). High-adoption schools (247.96), have more economic disadvantage than in low-adoption schools (257.50) and with non-adopters (267.60). The demarcation between high-adoption and low-adoption schools is statistically significant, with high-adoption schools experiencing more economic disadvantage.

A variety of outcome data can be found with these schools. First, cohort graduation rates were higher (93.21 percent) among non-adopters as compared to 86.50 percent among low-adoption schools and 86.24 percent for high-adoption schools ($p < 0.001$). Schools with higher graduation rates have less of a defined need for dropout prevention services. The adoption of the EWS indicates that these schools shared many aspects of the demand for the innovation. Many rural high schools were non adopters. As seen in the SLDS data, rural high schools in Montana tend to have higher graduation rates than town or city high schools. Schools in the last category (non-adopters) may not have a defined demand for dropout prevention policies. They may already have an intimate relationship with their at-risk students and may not need a tool to identify them.

The satisfactory attendance rate is the count of students who have a 95-percent average daily attendance rate divided by the total number of students enrolled. Satisfactory attendance ($p < 0.001$) rates are higher among non-adopters (49.24 percent) as compared to low-adoption (40.39 percent) and high-adoption (40.16 percent) schools. These findings highlight challenges faced by these schools. As expected, schools with lower satisfactory attendance rates have a higher proportion of students with chronic absenteeism issues. This demand may have driven the interest in and valuation of the EWS tool and its findings.

Variation is also noted in assessment scores. Students in non-adopting schools are more proficient (50.71 percent) on the English language assessment (ELA) assessment in grades three through eight than their peers in high-adoption (44.43 percent) and low-adoption (42.88 percent) schools ($p = 0.002$). The trends regarding the ACT composite (the 11th-grade statewide assessment) average are also statistically significant ($p = 0.02$) and show that the non-adoption group scores higher (19.54) than the low-adoption (18.54) and high-adoption (18.72) schools.

Across all indicators, non-adoption schools stand out as having less of a defined demand in their schools for an EWS. This addresses how the school prioritizes dropout prevention and the use of the EWS tool, while raising issues with the scope and scale of the EWS program. Interview evidence suggests that the scale of the EWS program has eclipsed, signaling that higher levels of demand are shown by schools that have already shown interest in the tool. There are important differences between these groups. Non adopters are more rural and tend to have less economic disadvantage than their peers. Many EWS adopters are from towns which have greater degrees of economic disadvantage. The student outcomes measures show that despite their disadvantage, high adoption schools had stronger outcomes than low adoption schools. What created the bar between these schools is this profile of demand which informed the progressive development of the Montana EWS program. This bar suggested differences based on if schools had a demand to use the dropout prevention data.

5.3 What policy changes occur in schools that have used EWS in their intervention model?

5.3.1 Summary table

*In high adoption schools, teachers are paid more and stay longer in their positions
*Variation in student outcomes did not predict upload frequency
*Higher per pupil ratios predicted higher upload counts
*High adoption schools communicate the school's dropout prevention program and EWS data to all staff members
*Schools with longer exposure to the EWS tool focused on the development of a data culture around dropout prevention,

Interview respondents from small high-adoption schools remarked that the intimacy of their schools allowed for close relationships between students and educators, easy dissemination of data from school leaders to educators, and personalized interventions focused on unique student and family needs. Since respondents knew their students, they did not

Table 2 Teacher variables and per pupil expenditure

	High adoption	Low Adoption	Non- Adoption	F	Significance
Teacher Mean Salary	$49,291.37	$45,625.14	$40,211.72	35.612	0.000
Per Pupil Expenditure	$14,459.83	$15,754.57	$16,964.73	4.995	0.007
Years Teaching	9.07	8.89	8.79	4.468	0.012

necessarily need the tool for early identification. Rather, they were interested in monitoring as a means of determining when to change course or end a given intervention. These schools often had between 150 and 450 enrolled students and were situated in economically challenged communities. Despite adversity, administration and faculty closely sponsored dropout prevention and used it in contexts where a student demonstrated need. These communities had rich administrative and faculty resources as evidenced by low pupil-teacher ratios, longer faculty tenures, and relatively high teacher and administrator salaries as compared to other disadvantaged schools in the low-adoption category (Table 2).

What made these schools stand out and differ from other rural schools? The association between mean teacher salary and the incidence of upload is strong with higher teacher salaries, suggesting that these schools upload and use data more frequently ($p < 0.05$). The association between mean years teaching in the same school and upload count was also strong, indicating that schools with teachers who have been teaching at the same school the longest also tend to upload and access the EWS data more frequently ($p < 0.05$). In comparison, the student-outcome variables (such as Smarter Balanced, ACT, and the school's mean dropout probability) did not predict the incidence of upload. Finally, schools with a longer history working with the program adopt more intensive intervention strategies, which may move the needle on achievement by greater degrees over time.

Also, these high adopters stood out in the way dropout prevention policy was implemented. Schools seem to identify demand for the innovation in tandem with developing a vision for the tool's implementation and determining a valuation process for its use. Among high-adoption schools in Montana, the vision and value of the tool originates from the school leader, in the context of an intervention team. This creation and composition of the intervention team is one marker of how well the vision and value is shared. It is exactly the process of meeting identified needs, finding value, and frequently returning to the data—demonstrating the intensity of data use—that determined the distinction between different kinds of adopters for schools in all locales. Among high-adoption schools, this involved formal dissemination of EWS data to all stakeholders of the school's intervention team.

One mediating factor to EWS dissemination is the degree a school has instructional and non-instructional staff participating in the innovation. To explore the hypothesis that the presence of faculty and certain non-instructional staff is related to the frequency with which a school has shared EWS data with the Montana EWS, we explored five different regression models to see how much, for example, the incidence of upload might be explained by the pupil/teacher ratio. Since schools must provide data to generate and refresh Montana EWS results, the frequency of upload is critical. It's one marker of the intensity of EWS data use. We found that the pupil/teacher ratios have a moderate association with upload frequency ($r^2 = 0.230$): The higher the pupil/teacher ratio, the more likely a school would upload more frequently.

Schools often face significant enrollment, staffing, and fiscal challenges, which can cause classrooms to become crowded, especially in disadvantaged communities. Lower pupil/teacher ratios could yield a more intensive teacher focus on dropout prevention. As seen in the interviews, intensive faculty engagement did occur, though not in all cases, which may have been mediated by class size. We also looked at counselor, psychologist, social worker, and librarian ratios and found that they explained little of the variation in average uploads per year. This indicates that staffing did not drive upload; however, other factors driven by school leadership did impact uploads, such as vision, value, and communication or the ways the school valued their staff.

The common theme behind policy implementation was communication. Communication is a key indicator of the degree of institutionalization of the EWS and dropout prevention as discussed during the interviews. One school leader describes communication as key to the process of assigning interventions. When designing early interventions, he talks to staff to get perspective on each student's circumstances, then looks at the data and verifies its accuracy with staff. He also engages the families in the process, something frequently done with the support of Montana EWS data. Building meaningful relationships is important for him because they're critical when finding a student an ideal mentor or defining the resources available for any given intervention. In the end, the goal is to increase student engagement by finding meaningful data-informed supports unique to each student and situation.

In schools with more than 6 years of experience with the EWS, there is a clear linkage between the diagnostic tool and the intervention, where users more frequently claim this link occurs most of the time ($p = 0.031$). This may indicate that schools with longer exposure to the EWS tool focused on the development of a data culture around dropout prevention, which reportedly takes time and vision. They were also more likely to use the MTSS committee to address attendance and academic matters impacting dropout prevention. Variation is also found in the degree of follow up (intensity of the intervention): Small schools are more likely to follow up than medium (greater than 450 students) and large (greater than 850 students) schools.

One principal summarized the kinds of interventions in their school (which are common in other schools that were interviewed): "We have some one-on-one support in the classroom, with a push-in model with paraprofessionals. We have pull-out support in a traditional fashion, in which kids are pulled out for support one on one and in small groups (quieter, least-restrictive setting). We have tutoring support, especially in Title 1 and Special Education, where they work on specific skills, gaps, and deficits to help build that background so that they can remain in an inclusive classroom and receive core instruction. Sometimes, it's not traditional. We are using an intervention aid, where our kids check in early in the morning." Goalsetting is a hallmark of MTSS programs, helping students develop academic goals based on their strengths and create measurable markers in pursuit of that goal. Evidence-based research shows the efficacy of these programs that focus on building relationships and increasing student engagement [4]. At its most effective, mentoring involves building a strong relationship and fostering a student's sense of belonging in the school community, while providing structured support for academic goals.

Vision, values, and communication are the soft traits of the successful Montana EWS intervention. This occurred in the context where high adoption schools valued teachers as seen in higher rates of retention and teacher compensation. They may have also been addressing more issues surrounding dropout as evidenced by high average dropout probabilities in comparison to low adoption schools. What made the difference is that high adoptions school choose to intervene more frequently that low adoption schools and certain institutional factors defined their use of the data. One institutional factor is the support of local MTSS processes.

6 Discussion

The MT OPI developed an EWS containing data on dropout risk, probabilities, and related risk factors, such as academics, attendance, behavior, and mobility. The SEA also provided school support focused on the range of interventions available; how to define a threshold; and when, and in what ways, to act on the data.

Professional development occurred at conferences such as the Montana OPI Summer Institute or the MT OPI Assist Conference, and with targeted data coaching to high-need schools provided by Montana EWS staff members as well as OPI specialists in Early Warning Systems. Successful implementation is seen when policy changes become apparent and serve to institutionalize practices. Data use did, indeed, occur, and in many cases went beyond early identification and embraced strategies to modify or end an intervention. In Montana, this data use is characterized by the communication of vision, value, and data to all stakeholders: As interviews revealed, this especially occurred in high-adoption school models, illustrating the impact of policy choices, local controls, and demand for innovation in many of these schools. Schools that decided to fully implement the Montana EWS had clear dropout prevention plans that framed data use and received SEA support in the process. Montana SLDS data clarifies that these schools also had increased capacity, as evidenced by longer teacher tenure and higher teacher compensation. Teachers in high-adoption schools were both more experienced and valued by school leadership.

Thresholds vary for the EWS indicators in different contexts [8]. In the case of Montana, these thresholds are established and monitored by schools who can tie the data to an intervention and follow data-informed best practices. Within a system, there are tradeoffs between accuracy, complexity, and identification of clear outcome measures [8]. Often, this tradeoff comes at the point that data is tied, or not, to an intervention. Of respondents, 48.28 percent said they use data to identify students less than 50 percent of the time, indicating that, even when a decision is made to intervene in low-adoption schools, the decision doesn't necessarily consider available data.

Framing the root causes and establishing intervention thresholds for students at risk of dropping out is challenging. Dropout rates are influenced not only by individual success in coursework and personal choices, but also by the context of schooling itself. Academic, attendance and behavioral risk factors can either contribute to dropout or be seized as opportunities [9, 10]. Utilizing data-informed decisions, educators can strategically intervene and provide tiered support to help students graduate. As discussed by interview respondents, this is found with high-adoption schools, which made the most use of the Montana EWS data and tailored their school's dropout response accordingly. In fact, differences between levels of adoption reflect the opt-in nature of the Montana EWS program: High-adoption schools identified need, pursued alternatives, chose to use the EWS, and committed to the process.

There were different levels of adoption, which included schools experimenting with alternatives to the tool in their dropout prevention model. There was no SEA mandate to use the Montana EWS. Rather, the SEA offered the tool and provided professional development regarding its usage. The SEA professional development provided guidance about data usage and insight into what triggering events will initiate, revise, and end an intervention.

The question remains, however, as to the degree to which interventions are data informed. In many cases, high adopters are most closely aligned with the requirements of an effective implementation, as defined by the increased ability to address dropout in their schools. Many high adopters noted that the ability to address dropout in a systematic fashion had been missing prior to their involvement with the Montana EWS. In these schools, users took the data and communicated it to all members of their dropout prevention team, including teachers (formal).

7 Implications

The focus of an EWS is not just accumulating data on risk factors or dropout probability; the crux of the system is determined by what users decide to do with the data accumulated (process). Data use can occur in multiple stages, from identifying potential non-completers to assigning interventions using locally defined thresholds to monitoring interventions once implemented to reassigning interventions based on available data. In addition, sometimes dropout-prevention programs are more intensive, in the case of a grade-level or schoolwide program implementation for instance.

Scale varies, though it is important to note that scale should meet the identified vision, value, demand, and capacity in the school for an EWS to be successful. This scale varies in Montana between high-adoption schools. While perceptions regarding the vision and value of the data are similar with each of level, the intensity with which data-informed practices are delivered differentiates them. This is seen acutely with the incidence of progress monitoring using the tool. It reflects differences in both delivery intensity and the depth of the data culture. High-adoption schools tend to use the EWS tool more frequently in progress monitoring (the decision to continue or end support), but not in all cases.

Unfortunately, some schools do not place an emphasis on dropout prevention. Interview respondents from three schools were not familiar with MTSS processes, including dropout prevention tied to behavioral strategies. When asked whether they focus on dropout, two of these schools had dropout prevention program grants from other sources that recently ended. There was little institutionalization of the lessons learned from the grants or follow through that consistently addresses dropout prevention.

In professional development activities, respondents claimed that the SEA should continue to create a clear tie between the EWS and MTSS intervention strategies and expressed optimism in the use of EWS tools. Specific state agency support could include additional assistance on establishing local thresholds for triggering and monitoring an intervention.

Overall, interview respondents expressed the need to adjust their processes to make them more relevant post pandemic and to target resources to those at-risk students for whom an intervention would likely have the greatest impact. The tenor of the responses among high adopters focused on the need to reshape the data-use model to address the remaining 25 percent of the student population that tends to have a volatile risk profile.

8 Limitations

This study faces one limitation. The response rate in the survey data was relatively low. We identified 154 active individual users of the Montana EWS from schools that used the EWS system in 2019. In 2022, when the surveys took place, there were fewer users that were knowledgeable of data use prior to the pandemic (based on which emails were received and if the person was in the same position). The survey had 36 responses from principals and guidance counselors from thirty-six schools. For this reason, we used the survey data to confirm other data elements, including those found in the interviews and the SLDS data.

9 Conclusion

In this study, we focused on data use. Research by our team also addressed the tie of intervention to outcome (whether Montana EWS-inspired interventions is associated with an increase in graduation rates among at-risk populations). The analysis uses a difference in difference methodology to analyze the probability that cohorts of EWS students will graduate, in comparison to trends within the same schools over the past 12 years. This study found that there were increases among subgroups in graduation rates, particularly among Native students which experienced a 7% increase in graduation rates in high adoption schools.

High-adoption schools interviewed said vision from leadership pushed the model forward, and that their schools had made strides in the development of a data culture surrounding dropout prevention. These schools had an MTSS or school-based intervention team. In these schools, there was value placed on addressing the issue of graduation, the diagnostic tool, and the ability to follow through with the intervention process. SEA support focused on these high-adoption schools. Demand for the EWS is still apparent among both kinds of EWS adopters. However, we note that there are certain characteristics of high adopters, such as vision, value, and communication that coincided with higher levels of implementation. Renewed focus with high-adoption schools and targeted support to low-adoption schools based on the incorporation of MTSS models marks the way forward.

Acknowledgements The research reported here was supported by the Institute of Education Sciences, US Department of Education, through Grant R305S210011 to the MT OPI. The opinions expressed are those of the author and do not represent views of the Institute, the US Department of Education, or the MT OPI.

Author contributions RC is sole author of this article. RC coordinated and completed data collection. Administrative data collected from the Montana Statewide Longitudinal Data System.

Funding This research is supported by a grant to the MT OPI by the National Center for Education Research, IES, and US Department of Education.

Data availability Data is available upon request and approval. Only deidentified data following FERPA regulations is released. The approval body is the Data Privacy and Security Committee, Montana Office of Public Instruction.

Code availability Not applicable.

Declarations

Ethics approval and consent to participate The Office of Research Compliance at Montana State University approved this exempt study. Research was completed using guidelines establish by the MSU board.

Consent to participate Instruments for obtaining informed consent were approved by Montana State University. Informed consent was gained for the survey instrument and interview protocol.

Informed consent Following this research guidance, the Montana Office of Public Instruction gained informed consent for participants in the surveys and interviews. MT-OPI is the state educational agency for Montana. Under 34 CFR § 99.31 MT-OPI can collect student data and in certain conditions disclose student data. This study uses MT-OPI data provided internally to a staff member and no data was disclosed to a third party.

Accordance This study did not involve an experiment. The study did involve human subjects. Data-collection instruments were approved by the Montana State University Office of Research Compliance.

Bio Robin Clausen is passionate about identifying barriers that students may face in their schooling, including identifying economic disadvantage in school communities and determining ways that educators might lessen the incidence of dropout. He earned advanced degrees from the University of Colorado, Boulder and Penn State University.

Competing interests The authors declare no competing interests.

References

1. Data Quality Campaign. Using early warning system data to keep students on track toward college and careers: a primer for state policy makers. 2013. [Online]. Available: https://dataqualitycampaign.org/resource/using-early-warning-data-keep-students-track-toward-college-careers.
2. Marken A, Scala J, Husby-Slater M, Davis G. Early Warning Intervention and Monitoring System Intervention Guide. Chicago: American Institutes for Research; 2020.
3. Bruch J, Gellar J, Cattell L, Hotchkiss J, Killewald P. Using data from schools and child welfare agencies to predict near-term academic risk. Washington: Institute for Education Sciences; 2020.
4. Frazelle S, Nagel A. A practitioner's guide to implementing early warning systems. Washington: Institute of Education Sciences; 2015.
5. Koon S, Petscher Y. Comparing methodologies for developing an early warning system: classification and regression tree model versus logistic regression. Washington: Institute of Education Sciences; 2015.
6. O'Cummings M, Therriault S. From accountability to prevention: early warning systems put data to work for struggling students. Chicago: American Institutes for Research; 2015.
7. Faria A, Sorenson N, Heppen J, Bowdon J, Taylor S, Eisner R, Foster S. Getting students on track for graduation. Impacts of the Early Warning Intervention and Monitoring System after one year. Washington: Institute for Education Sciences; 2017.
8. Knowles J. Of needles and haystacks: building an accurate statewide dropout early warning system in Wisconsin. J Edu Data Min. 2015;7(3):18–67.
9. Jerald C. Identifying potential dropouts: key lessons for building an early warning system. ERIC, 2006.
10. Bruce M, Horning Fox J, Balfanz R. On Track for success: the use of early warning indicator and intervenetion system to build a grad nation. ERIC, 2011.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.