education policy analysis archives

A peer-reviewed, independent, open access, multilingual journal

epaa aape

Arizona State University

Volume 34 Number 7 January 20, 2026 ISSN 1068-2341

Montana Early Warning System for Dropout Prevention: Data Use, Mediating Factors, and Impact

Robin Clausen
Montana Office of Public Instruction

Christiana Stoddard
&
Andrew Hill
Montana State University
United States

Citation: Clausen, R, Stoddard, C., & Hill, A. (2026). Montana Early Warning System for dropout prevention: Data use, mediating factors and impact. *Education Policy Analysis Archives, 34*(7). https://doi.org/10.14507/epaa.34.8700

Abstract: Early warning systems (EWSs)—predictive analytics used in dropout prevention—are now widespread and embedded in many student information systems and statewide longitudinal data systems. Few research studies focus on the processes and policies involved in using these kinds of data and how use may relate to graduation rates. In this mixed methods study of the Montana EWS (2012–2020), we assess the role of mediating factors associated with schools' adoption and use of the EWS for dropout prevention. We find that schools used the EWS more intensively based on school officials' vision, their perceived value of the EWS, broader dissemination of the EWS data, and when they placed more emphasis on relationship-building and professional development. We then examine trends in graduation rates in EWS-adopting schools. The results indicate that students in schools that used the EWS more intensively experienced improvements in graduation outcomes relative to

Journal website: http://epaa.asu.edu/ojs/
Facebook: /EPAAA
Twitter: @epaa_aape

Manuscript received: 16/4/2024
Revisions received: 22/8/2025
Accepted: 3/11/2025

students in non-adopting schools or in the same schools who did not receive an EWS analysis.
Keywords: predictive analytics; early warning system; dropout prevention; data use

Sistema de Alerta Temprana de Montana para la prevención del abandono escolar: Uso de datos, factores mediadores e impacto
Resumen: Los sistemas de alerta temprana (EWS, en inglés)—analíticas predictivas utilizadas en la prevención del abandono escolar—son ahora ampliamente utilizados y están incorporados en muchos sistemas de información estudiantil y sistemas estatales de datos longitudinales. Pocos estudios de investigación se centran en los procesos y las políticas implicadas en el uso de este tipo de datos y en cómo dicho uso podría relacionarse con las tasas de graduación. En este estudio de métodos mixtos del EWS de Montana (2012–2020), evaluamos el papel de los factores mediadores asociados con la adopción y el uso del sistema por parte de las escuelas para prevenir el abandono escolar. Encontramos que las escuelas utilizaron el sistema de manera más intensiva cuando los funcionarios escolares tenían una visión clara, percibían un alto valor del EWS, difundían más ampliamente los datos generados por el sistema y ponían mayor énfasis en la construcción de relaciones y en el desarrollo profesional. Luego examinamos las tendencias en las tasas de graduación en las escuelas que adoptaron el EWS. Los resultados indican que los estudiantes en escuelas que utilizaron el EWS de forma más intensiva experimentaron mejoras en los resultados de graduación en comparación con estudiantes en escuelas no adoptantes o con estudiantes en las mismas escuelas que no recibieron un análisis del EWS.
Palabras clave: analítica predictiva; sistema de alerta temprana; prevención del abandono escolar; uso de datos

Sistema de Alerta Precoce de Montana para a prevenção da evasão escolar: Uso de dados, fatores mediadores e impacto
Resumo: Os sistemas de alerta precoce (EWS, em inglês)—análises preditivas utilizadas na prevenção da evasão escolar—tornaram-se amplamente difundidos e estão incorporados em muitos sistemas de informação estudantil e sistemas estaduais de dados longitudinais. Poucos estudos de pesquisa se concentram nos processos e nas políticas envolvidas no uso desse tipo de dado e em como esse uso pode se relacionar com as taxas de conclusão escolar. Neste estudo de métodos mistos sobre o EWS de Montana (2012–2020), avaliamos o papel de fatores mediadores associados à adoção e ao uso do sistema pelas escolas para prevenir a evasão. Constatamos que as escolas utilizaram o sistema de forma mais intensiva quando os gestores escolares tinham uma visão clara, percebiam alto valor no EWS, ampliavam a disseminação dos dados gerados pelo sistema e enfatizavam mais a construção de relações e o desenvolvimento profissional. Em seguida, examinamos tendências nas taxas de conclusão em escolas que adotaram o EWS. Os resultados indicam que os estudantes em escolas que utilizaram o EWS mais intensivamente apresentaram melhorias nos resultados de conclusão escolar em comparação com estudantes em escolas que não adotaram o sistema ou com estudantes das mesmas escolas que não receberam uma análise do EWS.
Palavras-chave: análise preditiva; sistema de alerta precoce; prevenção da evasão escolar; uso de dados

Montana Early Warning System for Dropout Prevention: Data Use, Mediating Factors, and Impact

Early warning systems (EWSs) – predictive analytics used in dropout prevention – have gained traction across states as a strategy to predict and mitigate high school dropout risks among students. These systems analyze student level data to identify and monitor whether students are on- or off-track for graduation. The assumption behind EWSs is that the propensity to drop out is a gradual process and that educators can identify students early in the process, well before the end of a student's high school enrollment (Heppen & Therriault, 2008; Jerald, 2006; Knowles, 2015; Pierson et al., 2020). These indicators are intended to alert educators when an intervention is warranted, which tier of interventions are appropriate, and whether an intervention should be adjusted or discontinued. This allows resources to be targeted to students most in need of intervention support.

During the last decade, there has been a broad-based movement by the Statewide Longitudinal Data Systems (SLDS) grant program (funded through the National Center for Education Statistics) to incentivize state education agencies to coordinate readily accessible EWS data at the school level. EWSs are now widespread as many student information systems and statewide longitudinal data systems have embedded these tools. Typically, states implementing their own EWSs first identify and validate EWS indicators and then customize data tools for districts and schools within the state. State officials also provide support for EWS-based interventions (O'Cummings & Theriault, 2015). Access to an EWS within a SLDS has served to democratize access for districts that do not have the capacity to analyze dropout prevention data or the time to construct a system themselves.

This study examines the experience of implementing a state-developed EWS in Montana. Montana's state education agency, the Office of Public Instruction (OPI), developed and piloted its own EWS tool in a subset of school districts beginning in 2012. In 2015, the tool was made available to all school districts in the state. Adoption of the state EWS is voluntary, and there are no requirements that districts using the EWS achieve certain graduation targets or another specific outcome. Administrators also make their own decisions about whether to incorporate professional development and outreach into their use of the EWS, how to communicate the value of the tool, and how to disseminate the EWS data.

We examine the experience of adoption and the trends in graduation rates from 2012 through 2020, ending our analysis prior to the pandemic-related school closures during the 2019/2020 academic year. Our analysis addresses four main research questions:

(1) How are the characteristics of adopting districts different from non-adopters?
(2) What implementation processes do stakeholders report?
(3) What mediating factors influence dropout policies?
(4) Did EWS-adopting schools experience changes in their high school graduation rates relative to non-adopters?

The first part of the analysis is based on surveys and interviews with school administrators about the processes school personnel relied on to implement the EWS. These interviews address the alternatives in Montana that school leaders consider when planning dropout prevention and the perceived value and vision of "why" use the EWS. The survey addresses the "how" and principal opinion of their schools' use of the EWS and the Montana EWS program. In the second part of the analysis, we examine the relationship between school use of the EWS and high school graduation rates. We use anonymized student-level data and analyze changes in pre- and post- adoption graduation rates relative to trends in non-adopting schools.

Literature Review

Previous research has established that it is possible to identify students that are in danger of dropping out using individual and school-level indicators (Frazelle & Nagel, 2015; Marken et al., 2020; O' Cummings & Therriault, 2015). Early warning systems (EWSs) rely on the premise that the process of a student dropping out is a gradual process and contributing factors can be identified and monitored early on. Most of the models in use today rely on the "ABC" risk factors to generate dropout risk predictions: attendance, behavior (typically disciplinary incidents), and coursework (grades and credit accumulation; Allensworth, 2013; Koon & Petscher, 2015). In general, EWSs use a statistical model to convert a set of student-specific indicators into a simpler metric for assessing risk of drop-out, such as a binary indicator for "on-track"/"off-track" or "above"/"below" a threshold value. At other times, they generate a risk score. EWS models are typically implemented as universal screenings assessing all students in a school, although the tool may also only be used on subsets of students. An EWS may use current, contemporaneous data, as well as data from the past year or years.

There is now a large body of studies that find that EWS indicators that use 9th grade attributes (or earlier) do well in predicting relative dropout risk (Aguiar et al., 2015; Allensworth & Easton, 2005, 2007; Balfanz et al., 2007; Bruch et al., 2020; Carl et al., 2013; Christie et al., 2019; Gwynne et al., 2012; Sansone, 2019), although few studies showed lower predictive power for some groups, like newcomer English learners (Duessen et al., 2017).

Assuming a model identifies students sufficiently early, effective interventions can be implemented at critical points in a student's educational trajectory (Bruce et al., 2011; Hudson-Holness et al., 2022; Norbury et al., 2012), potentially improving the efficacy of these interventions (Sepanik et al., 2021; Sletten et al., 2022).[1] Many dropout prevention programs over the last 40 years have had disappointing results (Wang et al., 2025). The low efficacy may be due in part to poorly targeted interventions. For example, some dropout prevention programs may focus on providing interventions to an entire school or a grade level rather than focusing on those students most in need, reducing the potential impact of the intervention. Alternatively, the dropout prevention program may simply miss some at-risk students; school leaders subsequently perceive these students as likely to graduate, they do not receive support services, and they subsequently drop out. Proponents of early warning systems argue that without an EWS, school officials may not accurately assess students' dropout risk and provide appropriate resources. This is especially likely for students who do not have prior behavioral issues (Bowers et al., 2013) but have other indicators of dropout risk.

However, there are many ways to implement EWSs. For example, local policies and contexts influence the specific thresholds that would result in interventions. The locally defined thresholds can also prioritize which factors to target, as students may not exhibit risk in all areas. For example, a student with low attendance rates may be provided with a system of attendance incentives rather than incentives related to behavior or coursework. This means that attendance behavior, and coursework support may be provided to students at different rates over time given the demands of the intervention and local capacity of the system (Bruce et al., 2011). Furthermore, in some cases an EWS is embedded in a multitiered system of support (Kearney & Graczyk, 2020, 2022), while in others a single point person or a specified coach implements the EWS (Mac Iver et al., 2019).

---

[1] One caveat is that an EWS can falsely flag students who are not at risk. Balfanz and Byrnes (2019) examine several different studies and conclude that roughly 1/3 to 1/5 students identified as at risk, but in fact graduate without other interventions.

Previous studies of the adoption of an EWS provide some insight into implementation, but most focus on single schools or districts and do not focus on statewide adoptions (Faria et al., 2017; Marken et al., 2020; O'Cumming & Thierrault, 2015). Marken et al. (2020) notes that EWS school leaders should compare the fidelity of their model to established research based on duration, quality of delivery, program specificity, and student engagement. This requires educators to have the capacity to evaluate if their school or district met its goals, if the use of evidence-based practices enabled success in the intervention, and an assessment of the data culture and the role of the EWS. However, few studies have investigated statewide implementation where districts can vary in the extent to which they adopt an EWS and the processes involved in implementation. As a result, state-level policymakers may make ad hoc decisions about implementation without understanding the factors that other states have identified and worked through.

Background on Montana's EWS

Montana's Office of Public Instruction (OPI) developed its research-based predictive model for their early warning system (EWS) with a goal to foster local environments that reduce dropout rates. The system also uses "ABC" risk factors described above: attendance is measured as days present/days enrolled, behavior is measured by in-school suspensions, and coursework indicators are credits and grades. The system also includes data on student mobility (number of transfers in the past year). The system uses both contemporaneous data and past school-year snapshots. The Montana EWS model does not factor in race/ethnicity or other student characteristics (e.g. free/reduced status, disability, or English language learner status). By focusing on attendance, behavior, and coursework, the system predicts risk independent of demographics, economic disadvantage, or other factors that may be out of a student's control (e.g., foster care or disability). The EWS model calculates a "risk score" using a logistical probability regression model. To calculate a risk score, school officials must upload school- and student-level data, and the locally provided data is combined with state-level data. The model generates a dropout risk score between 0 and 1, and the model flags students as "at risk" if the score is above a 0.15 probability of dropout or as "extremely at risk" if the probability is 0.35 or higher.

The Montana OPI piloted the EWS in 2012, in a set of schools that were chosen to be somewhat representative of the state. The pilot schools were provided with a high level of support from OPI, including one-on-one data coaching from a dedicated data coach. State officials also included a database administrator and a program manager. Beginning in 2015, all schools in the state could opt to use this program with the program manager conducting outreach to non-participating schools. Prior to that, the student information systems in use in the state did not provide a commercial product that could be used instead of the state EWS. As noted, our analysis considers outcomes through the 2018–2019 school year to avoid pandemic-related changes, especially to in-person school attendance.

The Montana EWS program is currently not required by the state. There is no cost to participate. Beginning in 2015, outreach campaigns raised awareness of the Montana EWS, the benefits of the system, and its requirements. OPI also promoted the EWS at a variety of local and regional conferences with a focus on encouraging principals to integrate the tool into dropout prevention processes. OPI updates the model annually and provides outreach and professional development to participating schools. The OPI-sponsored professional development incorporates three tiers for interventions in the state: Tier 1 – normal classroom instruction, Tier 2 – small group supports, and Tier 3 – the most intense engagement with the student including coaching or mentoring. There are no program requirements for adopting the EWS, and schools that adopted the EWS were not required to participate in this evaluation.

District officials make the decision to adopt the EWS. However, in Montana, nearly all the high school districts only include one school.[2] Consequently, the principal is often also the district superintendent. School principals have significant latitude to make decisions about whether to use the tool and how often to upload data and update risk scores. Consequently, there is considerable variation in implementation processes among adopting districts. In the case of many Montana schools, the principal also determines which interventions are prioritized.

Data: Administrative, Interviews, and Surveys

Administrative Data

The administrative data used in this case study is from the Montana Statewide Longitudinal Data System (SLDS), which was accessible to the research team.[3] The SLDS data includes information for all students on race/ethnicity, gender, age, graduation and dropout status, attendance, achievement, and student mobility. For students whose data was loaded into the EWS, the data also includes all EWS risk scores and the dates these scores were generated.

School characteristics used in the analysis include enrollment (total and by race/ethnicity and gender), mean teacher salary and teacher tenure (a measure of experience), cohort graduation rates, post-secondary enrollment rates, dropout rates, attendance rates, ACT composite mean, and the school-level Title I status (e.g. comprehensive, targeted, or universal). District-level data includes per-pupil current expenditures. The administrative data also includes measures of local economic disadvantage, locale characteristics, and demographics. One measure of economic disadvantage for the school is the Spatially Interpolated Demographic Estimates (SIDE) provided by the National Center for Education Statistics, which takes a geospatial approach to assigning income to poverty ratios for a school community based on the physical addresses of students. The measure is normalized so a ratio of 100 indicates that the school community is at the poverty level as based on American Community Survey data. A second measure of disadvantage is the percentage of students eligible for free and reduced-price lunches.

As noted above, the administrative data also contains information related to the EWS. Specifically, for EWS-adopting schools, it includes the EWS-generated student dropout probabilities and the number of times and dates the school uploaded data into the EWS. We categorized EWS schools into high adopters (more than three uploads of local data/year – quarter), low adopters (two or less uploads/year - semester), and non-adopters (no uploads in current year). See Appendix A1 for a comprehensive list of all variables in the administrative data.

Interviews

The research team invited school officials to participate in group interviews to better understand the way the EWS was implemented. Of the 62 districts that participated in the EWS in 2019, 18 responded to the email outreach invitations, and the research team selected 15 middle and

---

[2] Of the 172 high schools in FY 2019, most are districts with only one high school. Only eight districts, all high school districts, have more than one high school, of which four were EWS districts.

[3] Student-level data from the SLDS was deidentified before the analysis: names were removed and student ids were replaced with anonymized ids that still allowed individual records to be merged across years. This procedure was defined in the data sharing agreement with Montana State University and it was approved by the IRB of the institution.

high schools to participate[4] to represent diverse schools and communities. Eleven of the participating high schools were small to medium-sized (less than 850 students), and nine were primarily rural. Five of the participating high schools had a high proportion of Native students in on-reservation communities.

When these interviews were conducted in 2022, nine of the schools were using the state EWS. Of these, five had used the Montana EWS for at least seven years. Four additional schools were using vendor EWS models in 2022, primarily Infinite Campus, but they had used the Montana EWS during 2019 (the last year of data used in this study). Two additional schools in the interview sample had never used an EWS before and were considering options for a provider.

The groups had an average of two participants per interview for the 15 interviews with a total of 36 participants. These included high school principals as well as additional participants selected by the principal who had used the EWS (attendance secretaries, school counselors, teachers, and librarians). Interviews were conducted over Zoom for an hour. Each school received a $2,000 incentive to participate in the study in funds that were earmarked for their dropout prevention programs. Each interview respondent was asked twenty questions from a battery of 35 questions. All questions were asked at least five times (see interview protocol in the Appendix A2).

In the design phase, we defined school processes and factors to measure, including motivation to participate in the program, support provided by the SEA, contextual and institutional descriptors, and student outcome factors. Interview questions focused on how intensively EWS was used, how the data were reviewed and disseminated, the perceived value of the tool, the associated benefits and costs, and how the school intervened with at risk students. The interview protocol is included in Appendix A2.

Survey

In addition to the interviews, we also sent surveys to the 154 school users in 55 districts that had an active EWS profile and valid email address in May 2022. The survey questions asked about how often EWS was used, the data dissemination process, whether EWS results were linked to interventions, and the way interventions were tracked. Most of the questions were closed-ended, with two prompts soliciting open-ended responses. The survey protocol is included in Appendix A3.

The sampling process was purposeful between groups (types of districts/schools) and random within groups (who in the district responded to the survey). Invitations were sent to superintendents, building leaders, counselors, and all staff that have access to their district's SLDS profile in 2022. The response rate was 23%. Response rates were likely affected by several conditions. First, approximately one-third of school- and district-level users opted out of automated emails from the SEA (GovDelivery). Second, the list contained invalid email addresses or bounce backs because of employment termination, often the transfer of an employee to another school system. The response rate may also have been affected by the rules at the Montana Office of Public Instruction about repeated emails to survey participants, which is limited to two emails per campaign. Finally, response rates to the survey may have been shaped by the lack of a program requirement to participate in evaluation activities, respondent familiarity with the EWS, questions about the appropriate person to respond to the survey, and perceptions regarding the current status of EWS related implementation in their schools or a school's length of participation in the program.

---

[4] Only 4 of the 62 districts participating in the EWS have multiple high schools in the district. Because principals had significant latitude in how the EWS is implemented, the interviews focused on principals, noting that principals could and did invite other school staff to participate. Many of the principals were in high school districts where they also serve as superintendent.

Methods

Quantitative Analysis

Our first research question asks how the characteristics of schools vary across the adoption groups. All EWS schools (62) were included in this analysis and comparisons focused on years prior to 2020. For categorical variables, we used chi-squared tests to gauge the statistical significance of differences across groups.[5] Adoption status is a categorical variable based on the number of times school officials upload the school attendance, behavior, and course grade data to the EWS tool to obtain the student-level risk probabilities. We classified schools into three groups: high adopters with more than three uploads of local data/year – (roughly quarterly); low adopters with one or two uploads per year, and non-adopters with no uploads in current year. The chi-squared analysis used to discuss mediating factors targets the different patterns of counts of schools by locale (category) between these three groups. The comparisons allow us to focus on patterns apparent between two categorical variables with common endogenous condition.

To investigate differences across groups in characteristics measured by continuous variables, we used a general linear model where the outcome was the dependent variable and level of adoption was the fixed factor. We report findings that are significant at the $p < .05$ level. When analyzing student outcomes, the dependent variable, e.g. attendance, was analyzed by fixed factors (including the categories based on intensity of use).

Qualitative Methods to Identify Processes and Mediating Factors

We use analysis of the interview and survey data to better understand the process of adoption, implementation, and the factors that led to policy changes by school personnel, research question 1(b)and 1(c). In the analysis of interview data, we identified themes for each interview and the relationships established between questions by respondents. We coded interview transcripts via inductive and deductive processes. The Zoom transcript was consolidated by comparing the transcript with the audio recording. At the same time, the responses were open coded (inductive) to allow patterns to be identified. 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 (Coates et al., 2021). The process is highly iterative and requires revisions to the study's procedures in line with emergent data and themes. Themes were identified based on the coding framework and subsequent revisions of the framework. A deductive last stage integrated survey and administrative data findings to include the themes identified in the interview.

Regression Analysis of Graduation Outcomes

The fourth research question asks how the graduation outcomes for students in adopting schools differ from those in non-adopting schools. To answer this question, we use regression analysis with two-way fixed effects that control for fixed school and cohort-grade-year characteristics (in the spirit of a difference-in-difference model). The first model we estimate includes annual data for all students in Montana high schools who started ninth grade between 2007–2008 and 2017–2018. This regression examines the relationship between a student being scored in the EWS and their eventual graduation:

---

[5] A chi-squared analysis is used to compare observed results with expected results. It is used when analyzing categorical data involving two or more variables that can share certain conditions in common (e.g. same assessment, same population).

$$(1)\ Y_{\{icgst\}} = \beta_0 + \beta_1 EWS_{\{icgst\}} + \beta_2 X_{\{igst\}} + \beta_3 S_{\{st\}} + \beta_s + \gamma_{c,g,t} + \epsilon_{\{igst\}}$$

$Y_{\{icgst\}}$ is measured either as four-year cohort graduation status or as year enrollment end status (senior year). The variable $EWS_{\{icgt\}} = 1$ if the student *i* in cohort *c* and grade *g* was loaded into EWS system in year *t*. The model includes student controls, X, and time-varying school controls, S.

The model also includes cohort by year by grade fixed effects, $\gamma_{c,g,t}$, and school fixed effects, β_s. School fixed effects control for all characteristics of a school that are fixed or common over time. These might include things like the overall economic climate of the area where the school is located or the general culture and norms of the school. The use of these fixed effects means that the β_1 coefficient is interpreted as the difference between graduation outcomes for students in adopting schools before and after the EWS was adopted each year. We also find that in some adopting schools, not all students are scored each year, either due to moves in and out of the school or due to selective use. The EWS indicator will therefore also vary within schools each year for scored and non-scored students, and β_1 will also be estimated using the variation in graduation outcomes for scored and non-scored students in the same school.

Graduation rates are likely to change over time even without EWS use, so only comparing graduation rates before and after EWS adoption could be misleading without accounting for these statewide trends in graduation rates. Consequently, the regression also includes cohort by year by grade fixed effects. This implies that any changes in graduation rates in EWS schools before and after adoption are estimated relative to trends in outcomes for the same cohorts in non-adopting schools.

Because schools may have used the model intensively and students who are scored more often may have been the more at-risk students, we also estimate the effect of EWS use at the school level. Our second set of regressions examine whether students in *schools* that used the EWS had different graduation outcomes, regardless of whether and how many times the individual student was scored.

$$(2)\ Y_{\{icgst\}} = \beta_0 + \beta_1 EWS_{\{st\}} + \beta_2 X_{\{igst\}} + \beta_3 S_{\{igst\}} + \beta_s + \gamma_{c,g,t} + \epsilon_{\{igst\}}$$

Note that this model is the same as (1), but the EWS indicator is measured at the school by year level, rather than the student by year level. We construct this indicator in two ways: first, we estimate the model based on whether schools used the EWS at all during the year, and, second, we estimate this for schools that used the EWS multiple times each year.

Findings

Differences across Schools by EWS Use

How did adopting schools differ from non-adopters? In general, adoption varied by year, and adopters tended to be larger and more economically disadvantaged. Table 1 shows participation by year beginning in 2015, when the EWS was made available to all districts in the state, through 2019. We focused on the pre-pandemic period due to differences in attendance, assessment waivers, and school closures during the pandemic period. The annual count of districts represents two major expansions of the program in the 2015–2016 and 2018–2019 school years. This included increased recruitment and an increased outreach by the SLDS team providing professional development and training opportunities. Districts that began to participate but curtailed their participation in the next year(s) were removed from future year counts.

Table 1
Early Warning System Annual Participation by District and Student

Year	Adopters by Year (Grades 3-12)		Non-adopters (Grades 3-12)	
	Districts	*Students*	*Districts*	*Students*
2015–16	47	15,792	334	66,515
2016–17	47	22,465	332	68,461
2017–18	48	18,849	331	69,620
2018–19	62	34,117	333	71,167

By 2019, there were 62 districts serving Grades 3–12 in the program. This compares to 333 nonparticipating districts. The adopting districts tended to be larger than the non-adopting districts. A total of 34,117 students in these districts had records uploaded to the EWS system, about a third of students in Grades 3–12 in the state. Within adopting districts, schools varied in how intensively they used the EWS. To assess intensity, we used the count of uploads generated by the Montana EWS system to categorize schools into a high adoption group (three uploads or more/year – quarter), low adoption group (two or less uploads/year - semester), and non-adopters (no uploads in current year). Table 2 shows the trends in the percentage of non-adopters, low adopters, and high adopters after the program was made available to all districts. Ninety schools uploaded at least three times in any given year. Six hundred schools that have students in Grades 3–12 never created an EWS profile or received Montana EWS support. Table 2 also shows how adoption varied by school size, with non-adopting schools being more likely to be found among the smallest schools as seen in a chi-square test ($p < .001$).

Table 2
Adoption Status (2015 – 2019)

	% of High Adopters	% of Low Adopters	% of Non-Adopters	Montana School Count (K-12)
Less than 150 students	22.22%	41.68%	72.83%	512
151 to 400	41.11%	31.06%	21.00%	204
401 to 850	26.67%	21.97%	5.83%	88
Above 850 students	10.00%	5.30%	0.33%	18
Montana EWS Total	90	132	600	822

Adopting schools also tended to be more economically disadvantaged based on a measure of neighborhood poverty (SIDE). Based on the average of the poverty ratio for every geolocated student address, we identified localized differences between EWS schools. The general linear model analysis showed that in high adoption schools there are significantly more economic disadvantages

(247.96) than in low adoption schools (257.50) and among non-adopters (267.60). These were statistically different (general linear model: $p<.002$).

Table 3
School Comparisons by Adoption Status

	High Adoption	Low Adoption	Non-Adopters	*F*	Sig
School Budget					
District Per Pupil Expenditure	$14,459.83	$15,754.57	$16,964.73	4.995	0.007
Staffing					
School Mean Teacher Salary	$49,291.37	$45,625.14	$40,211.72	35.612	0.000
School Mean Teacher Experience (Years Licensed)	9.07	8.89	8.79	4.468	0.012
Outcomes					
School Attendance Rate	0.40	0.40	0.49	19.018	0.000
School Post Secondary Enrollment Rate	0.39	0.41	0.46	2.108	0.125
School ACT Composite	18.72	18.54	19.54	4.029	0.020
Economic Disadvantage					
School SIDE	247.96	257.50	272.81	6.492	0.002

Approximately one-fifth of schools with high proportions of Native students (above 10%) were in EWS-adopting schools. These schools also received support through Title 1 and were classified as comprehensive and targeted support schools, making them eligible for additional OPI support including one-on-one data coaching training for school leaders about the EWS.

Factors Influencing Choice of EWS Tools

Our qualitative analysis of statewide implementation of the Montana EWS highlights the process-related mediating factors which show the requirements of the local models including how and why schools used the EWS. Many school level factors were shared by participating schools, including the Montana EWS algorithm and results, the school recruitment process, OPI data coaching and support for local implementation of the EWS, and incentives to participate in the evaluation. In Montana, mediating factors at the school level determined the scope of implementations, the variation in each school's practices, and the integration with Montana's Multi-Tiered System of Support processes or other programs for dropout prevention.

In Montana, some districts used alternatives to the state EWS for dropout prevention. We see this in the number of schools that no longer used the Montana EWS in 2022 and instead relied on a EWS tool provided by their student information systems. These schools had all maintained a Montana EWS profile between 2015 and 2020.

Many schools followed the 'do it yourself' model, as described by one interview respondent. This model involved an educator accessing data within their student information system, independently analyzing the data, and implementing policy as seen in the way the school targets resources and intervenes with students. This approach took staff time, resources, and focused leadership on dropout prevention, which many schools lacked. There may also have been a gap between early identification and intervention where school leaders noted that a student was identified but this did not lead to an intervention. Another example of a 'do it yourself' approach was in a large high school that designed a survey focused on socio-emotional indictors. This allowed educators to integrate socio-emotional topics (e.g., belonging) with questions about student opinions on dropout (e.g., what does at-risk mean). Smaller schools may struggle to implement such a strategy since there may not be the capacity to design, implement, and analyze reliable, normed survey data.

The other major alternatives to the OPI developed EWS were the tools in third party vendor systems. In Montana the largest providers were Infinite Campus and Power School. Respondents remarked that vendor led models are relevant to their situation in that they are integrated into the school's student information system. These tools also made it possible to update risk scores more frequently, given the availability of the data.

In the case of Infinite Campus, the EWS was first piloted in Kentucky and later expanded to other states. In states such as Nevada, it is now integrated into the state accountability system (Lieberman, 2024), with higher stakes in the use of the tool. Benefits of that model included additional risk factors beyond what the Montana EWS uses, a focus on daily risk prediction based on live data, and that users did not need to import or share data (Christie, 2019). The algorithm is frequently refined. It contained over 74 data elements involved in the calculation, compared to the simplicity of the Montana EWS with 24 variables. Drawbacks included the fact that support is limited to those districts that have the Campus Analytic Suite, which had a cost. There were also differences in the professional development and data coaching provided to end users when compared to the Montana EWS, with Infinite Campus support largely occurring by the vendor and Montana EWS support occurring with Programs and Data divisions at the OPI.

Factors Affecting the Process of Implementation: Vision, Value, and Dissemination

The survey and interview results showed that an important factor in adopting the Montana EWS was the perceived benefits/drawbacks of the tool as evident in the interviews. This value was often directly communicated by the principal, who also championed the vision of data use as to how the tool fits in the school community. The way that data was disseminated was also a factor. Some principals made their own local dashboards with the EWS data that were designed for use by counselors and teachers. Others choose not to distribute the EWS data. When discussing the value of the EWS, one principal commented that "the EWS is just a small picture of the bigger picture that we have with each kid." EWS data was often combined with other data points so that schools could identify thresholds of support and better target resources to those most vulnerable or to identify situations in which intervention was most likely to have an impact. As one principal stated,

> It gives us great access to information that really helps us identify those most at risk kids, so that our teachers can swoop in and do what they do best in terms of building relationships and helping that sense of belonging in school and by adding those supports and intervention pieces so that students have the potential to be successful.

Shared value of the Montana EWS was a factor for data driven dropout prevention in many schools that adopted the model. One principal noted that the point of an EWS "to go ahead and find solutions for problems that are actually solvable." The first step of this intervention cycle was the diagnostic tool and identifying where interventions can have the greatest impact. An important factor involving adoption was the presence of a Multi-Tiered System of Support (MTSS) team or a team of educators working on dropout prevention. As one principal noted,

> We are looking to expand our MTSS group into more things like attendance and grades and those kinds of interventions to catch students before they get a special referral. We are hoping that by reengaging with EWS data we can proceed down that path and develop prevention strategies.

Time with these intervention strategies, time using EWS data, and time spent developing this data culture was also important. As indicated above, there was also reengagement with the data following the pandemic. For example, schools with more than seven years of experience with the model returned to using the EWS more quickly than schools with less experience as seen in our survey (Pearson chi-square = 12.296, $p = 0.031$).

A shared vision rooted in the leadership of the school leader fostered the spread of many implementations. The degree to which this vision was communicated to counselors and faculty distinguished schools. Dissemination was seen in the number of people that had access to and reviewed the data. Most survey respondents reported that their school used semi-formal ways to disseminate data prior to an intervention. 'Semi-formal' was defined in the survey as at least one stakeholder reviewing the data prior to an intervention. Semi-formal methods were more predominant in low adoption schools. In these cases, counselors and teachers likely did not have access to the data. In most high adoption schools with two or more data uploads a year, dissemination was detailed and did reach the counselors and teachers. Based on interview reports, dissemination was highly localized. High adoption schools used the tool in a more formal way, such as within MTSS committee processes. In high adoption schools the formal process was designed to meet counselors and teachers' needs. As identified by a school administrator in the interview, "the key was to find a tool that is easy to communicate and let data turn into formal and informal conversations."

Mediating Factors for Adoption and Continued Use

How did schools translate the EWS indicators into policies to improve graduation rates?

Mediating factors identified by interview and survey respondents included the importance of the building leader, the importance of relationship building, and the cost-effectiveness of the Montana EWS.

Respondents frequently stated that local implementations were driven by the building leader. In most high school districts in Montana the building leader is also the superintendent of the district. Principals decided if interventions were EWS data informed and whether the engagement of the EWS tool led to reform based on early identification, data informed interventions, progress monitoring, and Tier 3 engagements. In low adoption schools, often this dissemination did not occur. With limited dissemination, faculty may not have access to the EWS data or know its value to the school community.

In contrast, interview respondents in five high-adoption schools indicated that relationship building, and student engagement were the heart of dropout prevention., and Tier 3 support. Respondents to the interview from small schools were asked questions about if they knew their students without having to use data support. Most respondents noted that they do know their students well, but they still prioritized the use of the tool. For that reason, in their assessment of student needs, the evidenced-based tool added value to their intervention processes. The tool enhanced faculty and staff input and provided a way to monitor change over time. Small schools were often at an advantage when compared with peers. Small schools participating in our survey were more likely to engage in follow up (Pearson chi-square = 4.360, $p < 0.037$), a marker of adjusting an intervention and deciding when to discontinue the intervention.

Respondents reported that using the EWS may have saved them money because they were able to target resources and support more carefully. For example, the EWS flags allowed them to identify lower risk students who were likely to succeed with Tier 1 support in the classroom rather than more intensive services. This process allowed the schools to address potential false alarms – students identified but noted to have less risk than other students. Administrators remarked that having a lower cost per student meant they were able to expand the scope of their dropout prevention services by providing more intense services for more at-risk students. One principal explained that the use of staff resources was often less than what would occur with alternative schooling. Many of the responses focused on targeting resources and identifying students most in need:

> …the EWS lets us target interventions to those kids that need it most. I am not sure if it costs any less than without the EWS. It allows us to be more effective because it can be targeted since we have data to decide who needs it most. It is a more efficient use of our intervention dollars because we can target it better. (Principal of a high adopter school)

Overall, schools used the EWS model at different intensities to design interventions. Many EWS schools who participated in the survey did not use the data when crafting an intervention and reported that they indeed intervened with EWS students infrequently, less than half of the time (48%). Thirty-nine percent of EWS schools did not use any data to intervene with their students and there were questions as to whether they intervened at all. Data from low adoption schools in both the interviews and the surveys can provide insight into what schools do in the absence of an EWS. Non engagement was one of those options. Future investigation is warranted regarding the frequency schools intervene with or without an EWS.

Regression Analysis of Graduation Outcomes

Next, we focus on how use of the EWS model was related to students' likelihood of graduation. Table 4 shows the results from the linear regression for Equation (1) estimating the relationship between individual student EWS use and graduation outcomes. The regression relates individual student graduation outcomes to whether the student was loaded into the EWS system during high school. We run this regression for all students who started ninth grade between 2007/08, five years before the EWS was implemented in the state, and 2017/18. The last ninth-grade cohort included in the analysis would have largely graduated in 2020/21.

As discussed in the methods section, the regression includes cohort by year by grade fixed effects and school fixed effects. The inclusion of school fixed effects implies that identifying variation comes from comparing graduation outcomes for students scored by the EWS to other students in the same school who were not scored by the EWS, the majority of whom were enrolled in the school in years when the school did not participate in the EWS. The cohort by year by grade fixed effects imply that the student-level effects of being uploaded into the EWS estimated in the model are relative to patterns in graduation outcomes for students in the same cohort, grade, and year in non-participating schools.

The within-school comparisons among students are also possible because some EWS schools choose to generate EWS scores for only a subset of their students. Reasons for this included end users not wanting to prepare an upload file for all their students, or end users only being interested in a portion of the students, often as a follow-up to a prior intervention. Students who moved into the school after the EWS was run would also be missing scores, and students who had scored in one school and moved into a non-adopting school would also lead to within-school differences in EWS scoring. Consequently, the results in Table 4 are not strictly quasi-experimental results as selection into being scored by the EWS may be related to factors that independently affect student graduation outcomes.

Table 4

Regressions Results: EWS and Likelihood of Graduation Standard errors clustered by school reported in parentheses

	Dependent variable: Student ever graduated		
Student loaded into EWS: time-varying, year-to-year	0.009 (0.007)	0.030*** (0.005)	
Share of years student loaded into EWS			0.029*** (0.008)
Female		0.026*** (0.001)	0.017*** (0.001)
Hispanic		-0.052*** (0.009)	-0.018*** (0.004)
Native American		-0.133*** (0.012)	-0.045*** (0.007)
Asian		0.040*** (0.006)	0.022*** (0.005)
Black		-0.039*** (0.014)	-0.021** (0.010)
School controls	None	School enrollment, share female, share of each racial/ethnic group, share FRPL, Title I	
Fixed effects	Grade, cohort entry year, year	School, grade, cohort entry year, year	

Note: Regressions contain all MT students in 9th grade cohorts beginning AY 2007-2008 to AY 2017-2018; student-year data observations.

Table 4 reports the coefficient estimates from this model. The first column shows that without any school level controls, there does not appear to be an association between being scored by the EWS and graduation—the coefficient (.009) is small and not statistically significant. However, once school and student characteristics as well as school fixed effects are included, the second column shows that students scored at some point during high school are three percentage points more likely to graduate than students from the same school who were never scored (either because the school did not participate in the EWS in that year or because the student was not scored).

The final column of Table 4 replaces the binary indicator for whether a student was scored with a measure of intensity of exposure to the EWS, the share of high school years the student received an EWS score. This varies based on when the EWS was adopted in the school and if the student moved schools. The results show that the share of years a student receives an EWS score in high school is also associated with a higher likelihood of graduation. As noted above, although we cannot give estimates a strict causal interpretation, this is consistent with the system working as intended. The fact that the EWS is associated with higher graduation rates *after* controls are included but not without controls implies that scored students have characteristics that make them normally less likely to graduate, but that the EWS is associated with a higher likelihood of graduation conditional on those characteristics. This may indicate that the most challenged students received interventions based on EWS data.

Table 5 reports findings from equation (2). The results in this table show that the association between EWS use and graduation is driven by high adoption schools. These regressions include the same student- and school-level variables as in Table 4, but the key EWS indicator varies at the school level rather than at the student level. When all EWS schools are combined regardless of how intensively or selectively the system was used, simply adopting the EWS at the school level is not significantly associated with graduation outcomes. However, cohorts of students in high adoption schools that used the program more than once in the school year were 0.8% more likely to graduate than in low adoption schools.

Table 5

School level effectiveness of EWS for low- and high-adopters

	Ever graduate (9th grade cohorts from AY 2007-2008to AY 2017-2018; All MT students)	
School ever used EWS: time-varying, year-to-year	0.004 (0.003)	
School loaded EWS multiple times: time-varying, year-to-year		.008*** (0.003)
Student controls	Y	Y
School controls	Y	Y
School, cohort, year, grade fixed effects	Y	Y
Unit of observation	Student-year	Student-year
N	426,174	426,174

The stronger association in high adoption schools could indicate that interventions are more effective in high adoption schools or that high adoption schools were more motivated to act after receiving the EWS scores. According to the survey, 48% of EWS schools did not use EWS data in most of their dropout prevention decisions. Moreover, 39% of EWS schools did not use any data to intervene with their students and there are questions as to whether they intervened at all. Given there are likely several systematic differences between high EWS adoption schools and no adoption schools, the coefficient in Table 5 should not be interpreted as the causal effect of the EWS alone, but rather as the effect of the combined differences between high adopters and no adopters, one of which is EWS use.

We also examined associations among subgroups of students. Native students were five to six percent more likely to graduate if they had an EWS score compared to their peers who were not scored, although the small numbers of Native students in the study sample meant that this point estimate could not be distinguished statistically from the main result. This trend was less robust for other race/ethnicity subgroups. Low-income students (eligible for free and reduced-price lunch) were one percent more likely to graduate if they had an EWS score compared to their non-scored counterparts, like the main results.

Limitations

There are several limitations to this study. First, the survey findings are based on a relatively small sample. The response rate on the survey was 22.73% out of a total of 154 people contacted. The low response rate makes it challenging to make comparisons between groups of stakeholders, for example, early adopters of EWS and later adopters of EWS when disaggregated by school size. Therefore, we often use survey data to reinforce observations from other sources.

Second, surveys and interviews were conducted in 2022 even though our study is primarily concerned with EWS adoption and use prior to 2019. The 2020 pandemic was a major disruption to education systems, and there may have been issues recalling information from before the pandemic. For example, it is not clear if users would say the same things about the tool prior to the pandemic compared to after the pandemic. This is a particular challenge when evaluating a program that had been initially implemented a decade earlier.

Third, although the regression model includes a rich set of controls, EWS use is ultimately not random, and the regression results estimating the association between EWS use and graduation outcomes cannot be interpreted as causal. While the regressions do control fixed differences across schools, some time-varying differences within schools, and for differences across student cohorts, the coefficient estimates may also reflect the impact of specific dropout interventions or other factors correlated with more intensive EWS use.

Finally, the identified mediating factors from the surveys and interviews were not operationalized in the regression analysis of graduation. To achieve this, our study would need stronger survey response rates or an interview protocol involving all schools being asked the same questions about the mediating factors. While mentioned in our research design, it quickly became apparent that these limitations did not allow quantification of the qualitative mediating factors.

Discussion and Implications

The continuous metric built into Montana's EWS helps prevent false alarms by establishing a gradient of dropout probability and allows educators to focus resources on those students whose success is the most challenged and/or where interventions can matter the most. Educators can prioritize interventions with their students based on this metric. It limits false alarms by helping schools create thresholds based on the risk score, prioritizing students that have higher risk scores for specific interventions. In addition to the continuous score, Montana's system also has flags for students deemed "at risk," when the dropout probability exceeds 15%, and "extremely at risk," when a student's probability of dropping out exceeds 35%. Many principals from high adoption schools discussed the difference between at risk and extreme at risk, noting the at-risk student population contained many false positives, while with extreme at risk students it was almost certain they needed intense support to graduate.

The Montana Office of Public Instruction had a twin strategy to foster adoption of data use to improve graduation outcomes among schools. This involved building and refining the EWS tool and providing one-on-one professional development to close the gap between data and intervention. Schools varied in how intensively they used the EWS tool. In interviews, high adoption and low adoption schools had marked differences in how the EWS had been implemented. Responses from the interviews indicated that many school administrators found benefit in the EWS model, and that value informed the process of crafting interventions. School leaders varied in how they fostered the schools' use of the tool. How principals communicated the data to their staff varied between schools. This is one element of the data culture that surrounds the use of EWS data. Data cultures focus on continuous improvement, stakeholder support, collaboration, the vision of the school leader, the value modeled by the building leader to make data relevant to the school, and the crucial role of a data coach or knowledgeable peer (Mandinach & Gummer, 2016). In many high adoption schools, a focus on the use of the EWS tool entailed an intense engagement with the data by faculty.

High adoption schools also emphasized communication with all stakeholders and making the EWS data readily available to frontline users. In low adoption schools, there were fewer opportunities for staff to engage with the data and consequently fewer chances to make data informed decisions as seen in the results of the survey. In these schools, the survey responses indicated little follow up or effort to tie data use to an intervention. In these low adoption schools, use of the EWS tool may have provided data on early identification, but this was only infrequently acted upon. In high adoption schools there was a focus on making decisions which were adjusted along the course of a student intervention.

The use of the Montana EWS predictions was highly associated with year-end dropout status in the high adoption schools, but not in low adoption schools. What distinguished between the two is the degree schools tied data to intervention and how that affected the likelihood of implementing dropout prevention strategies. The evidence from low adoption schools indicated that support for dropout prevention was different than in high adoption schools. This was found even in cases where other aspects of a school's data culture may be robust. For example, one user reported lack of support by district administration ended the EWS program in her school. Data-driven decision-making was cited by the district and commonly used, but not in the case of dropout prevention.

Support to build a data culture can include an articulated vision for data use, employing front line educators in decisions to intervene, accountability within the schools, and the development of a culture of collaboration. The degree that teachers were involved in the choice to intervene or decisions about instructional change distinguished low adoption from high adoption schools.

In this evaluation, we sought to identify the degree to which the treatment (the tool and OPI professional development) was implemented in these schools. The effects of the dropout prevention tool varied depending on frequency and intensity of use. Voluntary professional development was provided at local and national conferences and on demand by EWS users. Although the professional development was voluntary, OPI strongly encouraged its use, especially for dropout prevention. Our research indicates that this professional learning had merit, particularly the data coaching, especially when it is relevant to schools' needs with dropout prevention.

Another pattern that distinguished high adoption and low adoption schools was in the dissemination of EWS results. Low adoption schools took a semi formal or nonformal approach to disseminating the data. In either case, data was infrequently shared beyond the principal and school counselor. In contrast, in some high adoption schools EWS data was tied to an intervention and students were tracked through progress monitoring. Data was shared with non-instructional staff and teachers. When schools tied data to intervention it revealed the scope of the intervention, the ability to refine an intervention once in place, and it provided schools resources about how to end processes once the intervention was successful. Users were more likely to intervene because the model allowed them to monitor the incremental effectiveness of efforts with at risk students. This inspired users to frequently return to the data.

Conclusion

Montana is a local control state with most of the educational decisions made at the district or school levels. A voluntary intervention that has a small imprint and a large impact on policy and processes is invaluable. The Montana EWS shows that the success of these kinds of data tools depends on many factors. Use of this tool was voluntary, and monitoring use was not the goal of the state education agency. We found that the way the tool was used varied substantially across adopting schools. Forty-one percent of EWS schools were high adopters. The results suggest that the incidence of low adoption did not signify that the model did not work. Rather, the results suggest the importance of renewed outreach to support use of the tool no matter what alternative the district is using. In the context of this program, sustainability of support for the reform is needed. This could mean renewed support for districts in dropout prevention if they take a 'do-it-yourself' approach and support to schools that use a vendor EWS. This is especially relevant since the schools that have been in the program the longest tended to focus more on dropout prevention planning and implementation as seen in the surveys. The interview data suggests that school personnel's use of the tool may take time and renewed resources.

When comparing all identified students to other groups in the school with the same demographic characteristics but who were not loaded into the system, identified students were three percent more likely to graduate. This calls for an investigation of schools that focused on one group of students versus other students in the school that were never added to the system. Feedback from the interviews is that schools focused on those students that they were most concerned about. In some cases, there was implementation by grade level. Given these factors, we conclude this choice by schools to include or exclude students from the EWS system was highly varied with schools determining their own requirements of who should be included in the system.

For those students whose data was uploaded into the system, use of the EWS system was associated with an increased likelihood that these students would graduate. Overall, students in high adoption schools were 0.40% less likely to drop out and to stay in school than their peers in low adoption schools in the same year. These outcomes potentially indicate that the schools' dropout prevention efforts were effective. As noted, approximately one-fifth of schools with high proportions of Native students (above 10%) were in EWS schools who received support through Title 1 and were classified as comprehensive and targeted support schools. Moving the needle in the ways that OPI could have an effect in these schools is important as they tend to have some of the highest dropout rates in the state.

There is evidence that this process of engaging with the data does become more intense over time, even in low adopting schools. Intensity is seen in the survey data when early adopters report significantly more time spent using EWS data in comparison to their peers. Schools recognized the need and benefits of an EWS, acted upon that need, sought out a tool, evaluated the tool, and decided if it met local requirements. Once school leaders found this value, they took advantage of the tool and related professional development. The alternative to this tool was to rely on the time of counselors and teachers to identify data about each student. This can present increased administrative burdens. The Montana EWS consolidates data provided by schools and data from the SEA student information system to provide free, customized data solutions for educators. It may indeed take time, and an understanding of need, alternatives, scale, capacity, and priorities to make the Montana EWS successful in these schools.

Finally, we note that while the findings indicate differences between those schools that fully implemented the model and those schools that only used the data occasionally as a reference, this study cannot address all the potential differences between adopters compared with non-adopters. Future studies could use an experimental design to compare matched pairs of non-adopting and adopting schools and the rate of change in graduation rates in both treatment and control environments. The matching criteria could focus on socio-economic differences and access to an EWS to further enhance our understanding of the ways different types of schools use these tools.

Acknowledgement

The research reported here was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305S210011 to the Montana Office of Public Instruction. The opinions expressed are those of the authors and do not represent views of the Institute, the U.S. Department of Education, or the Montana Office of Public Instruction.

References

Aguiar, E., Lakkaraju, H., Bhanpuri, N., Miller, D., Yuhas, B., & Addison, K. L. (2015, March). Who, when, and why: A machine learning approach to prioritizing students at risk of not graduating high school on time. In *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (pp. 93-102). https://dl.acm.org/doi/10.1145/2723576.2723619

Allensworth, E. (2013). The use of ninth-grade early warning indicators to improve Chicago schools. *Journal of Education for Students Placed at Risk (JESPAR)*, *18*(1), 68-83. https://doi.org/10.1080/10824669.2013.745181

Allensworth, E., & Easton, J. Q. (2005, June). *The on-track indicator as a predictor of high school graduation*. ISBN: 9780972603560, 0972603565

Allensworth, E. M., & Easton, J. Q. (2007). *What matters for staying on-track and graduating in Chicago public high schools: A close look at course grades, failures, and attendance in the freshman year.* [Research report]. Consortium on Chicago School Research. Retrieved from ERIC: https://eric.ed.gov/?id=ED498350

Balfanz, R., Herzog, L., & Mac Iver, D. J. (2007). Preventing student disengagement and keeping students on the graduation path in urban middle-grades schools: Early identification and effective interventions. *Educational Psychologist*, *42*(4), 223-235. http://dx.doi.org/10.1080/00461520701621079

Bowers, A. J., Sprott, R., & Taff, S. A. (2013). Do we know who will drop out? A review of the predictors of dropping out of high school: Precision, sensitivity, and specificity. *The High School Journal*, *96*(2), 77-100. https://doi.org/10.1353/hsj.2013.0000

Bruce, M., Horning Fox, J., & Balfanz, R. (2011). *On track for success: The use of early warning indicator and intervention systems to build a grad nation.* Retrieved from ERIC: https://eric.ed.gov/?id=ED526421

Bruch, J., Gellar, J., Cattell, L., Hotchkiss, J., & Killewald, P. (2020). *Using data from schools and child welfare agencies to predict near-term academic risks* (REL 2020–027). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Mid-Atlantic.

Carl, B., Richardson, J. T., Cheng, E., Kim, H., & Meyer, R. H. (2013). Theory and application of early warning systems for high school and beyond. *Journal of Education for Students Placed at Risk (JESPAR)*, *18*(1), 29-49. https://doi.org/10.1177/016146812012201401

Christie, S. T., Jarratt, D., Olson, L., & Taijala, T. (2019). Machine-learned school dropout early warning at scale. In M. Desmaris, C. Lynch, A. Merceron & R. Nkambou (Eds.), *The 12th International Conference on Educational Data Mining* (pp. 726-731). Retrieved from ERIC: https://files.eric.ed.gov/fulltext/ED599217.pdf

Coates, W., Jordan, J. & O'Clarke, S. (2021). *A practical guide for conducting qualitative research in medical education: Part 2 Coding and thematic analysis.* AEM education and training. https://doi.org/10.1002/aet2.10645

Deussen, T., Hanson, H., & Bisht, B. (2017). *Are two commonly used early warning indicators accurate predictors of dropout for English learner students? Evidence from six districts in Washington State.* (REL 2017-261). Regional Educational Laboratory Northwest. https://files.eric.ed.gov/fulltext/ED573197.pdf

Faria, A.-M., Sorensen, N., Heppen, J., Bowdon, J., Taylor, S., Eisner, R., & Foster, S. (2017). *Getting students on track for graduation: Impacts of the Early Warning Intervention and Monitoring System after one year* (REL 2017–272). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Midwest. Retrieved from https://files.eric.ed.gov/fulltext/ED573814.pdf

Frazelle, S., & Nagel, A. (2015). *A practitioner's guide to implementing early warning systems* (REL 2015–056). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Northwest. http://ies.ed.gov/ncee/edlabs

Gwynne, J., Pareja, A. S., Ehrlich, S. B., & Allensworth, E. (2012). *What matters for staying on-rrack and graduating in Chicago public schools: A focus on English language learners.* (Research Report). Consortium on Chicago School Research. 1313 East 60th Street, Chicago, IL 60637.

Heppen, J., & Therriault, S. B. (2008). Developing early warning systems to identify potential high school dropouts. Retrieved from ERIC: https://eric.ed.gov/?id=ED521558

Hudson-Holness, D., Minchala, M., & Le, U. (2022). Improving student success in introductory chemistry using early alert and intervention. *International Journal of Research in Education and Science*, *8*(4), 752-764. https://doi.org/10.46328/ijres.2950

Jerald, C. (2006). *Identifying potential dropouts: Key lessons for building an early warning data system.* Retrieved from ERIC: https://eric.ed.gov/?id=ED499838

Kearney, C. A., & Graczyk, P. A. (2020). A multidimensional, multi-tiered system of supports model to promote school attendance and address school absenteeism. *Clinical child and family psychology review*, *23*(3), 316-337. https://doi.org/10.1007/s10567-020-00317-1

Kearney, C. A., & Graczyk, P. A. (2022, September). Multi-tiered systems of support for school attendance and its problems: An unlearning perspective for areas of high chronic absenteeism. In *Frontiers in Education*, *7*. https://doi.org/10.3389/feduc.2022.1020150

Klare, M. & Stevenson, B. (2016). *Early warning systems in transition annotated bibliography.* National Technical Assistance Center on Transition. Retrieved from ERIC: https://files.eric.ed.gov/fulltext/ED601051.pdf

Knowles, J. (2015). Of needles and haystacks: Building an accurate statewide dropout early warning system in Wisconsin. *Journal of Educational Data Mini*ng 7(3). https://doi.org/10.5281/zenodo.3554725
Koon, S., & Petscher, Y. (2015). *Comparing methodologies for developing an early warning system: Classification and regression tree model versus logistic regression* (REL 2015–077). U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Southeast. http://ies.ed.gov/ncee/edlabs
Lieberman, M. (2024). A state uses AI to determine school funding. Is this the future or a cautionary tale? *Education Week*. https://www.edweek.org/policy-politics/a-state-uses-ai-to-determine-school-funding-is-this-the-future-or-a-cautionary-tale/2024/02.
Mac Iver, M. A., Stein, M. L., Davis, M. H., Balfanz, R. W., & Fox, J. H. (2019). An efficacy study of a ninth-grade early warning indicator intervention. *Journal of Research on Educational Effectiveness*, *12*(3), 363-390. https://doi.org/10.1080/19345747.2019.1615156
Mandinach, E. B., & Gummer, E. S. (2016). *Data literacy for educators: Making it count in teacher preparation and practice.* Teachers College Press. https://doi.org/10.17763/1943-5045-86.4.607a
Marken, A., Scala, J, Husby-Slater, M., & Davis, G. (2020). *Early warning intervention and monitoring system intervention guide.* American Institutes for Research: Chicago.
Norbury, H., Wong, M., Wan, Y., Reese, K., Dhillon, S., & Gerdeman, R. D. (2012). *Using the freshman on-track indicator to predict graduation in two urban districts in the Midwest region. Issues & answers* (REL 2012-No. 134). Regional Educational Laboratory Midwest.
O'Cummings, M. & Therriault, S.B. (2015) *From accountability to prevention: Early warning systems put data to work for struggling students.* American Institutes for Research.
Pierson, A., Frazelle, S., & Mazzeo, C. (2020). Adapting and using early warning indicators in different contexts. *Teachers College Record*, *122*(14), 1-24. https://doi.org/10.1177/016146812012201402
Sansone, D. (2019). Beyond early warning indicators: High school dropout and machine learning. *Oxford Bulletin of Economics and Statistics*, *81*(2), 456-485. https://doi.org/10.1111/obes.12277
Sepanik, S., Zhu, P., Shih, M. B., & Commins, N. (2021). *First-year effects of early indicator and intervention systems in Oregon.* (REL 2021-097). Regional Educational Laboratory Northwest.
Sletten, M. A., Tøge, A. G., & Malmberg-Heimonen, I. (2023). Effects of an early warning system on student absence and completion in Norwegian upper secondary schools: A cluster-randomised study. *Scandinavian Journal of Educational Research*, *67*(7), 1151-1165. https://doi.org/10.1080/00313831.2022.2116481
Wang, Q., Hsiao, Y. Y., Hushman, C., & Armstrong, J. (2024). The effectiveness of dropout intervention programs among K-12 students: A meta-analysis. *Journal of Education for Students Placed at Risk (JESPAR), 30*(3), 193–223. https://doi.org/10.1080/10824669.2024.2342779

About the Authors

Robin Clausen
Montana Office of Public Instruction
robinlclausen@gmail.com
https://orcid.org/0009-0005-4212-0224
Dr. Robin Clausen is principal investigator of the study. He is a research analyst at the Montana Office of Public Instruction.

Christiana Stoddard
Montana State University
chrisstodd@gmail.com
Dr. Christiana Stoddard is a professor of economics at Montana State University.

Andrew Hill
Montana State University
andrew.hill6@montana.edu
https://orcid.org/0000-0001-7630-6151
Dr. Andrew Hill is a professor of economics at Montana State University.

education policy analysis archives

Volume 34 Number 7 January 20, 2026 ISSN 1068-2341

Appendix

Table A1

Administrative Data

	Student level	**School level**	**District level**
Variables used in EWS model to construct risk scores	PreviousDropout # of Absences in last 60 days # of Absences in last 90 days # of Behavior Events in last 120 days # of Credits per year # of Previous Term A's # of Previous Term F's AgeDiffDiffDate AgeDiffDiffDate2 Attendance Rate BehaveEvents120days		
Variables used in interview and survey analysis	--	Enrollment (total and by race/ethnicity and gender), mean teacher salary and teacher tenure (a measure of experience), cohort graduation rate, post-secondary enrollment rate, dropout rate, attendance rate, ACT composite mean, school level Title I status (e.g. comprehensive, targeted, or universal), school SIDE.	Per pupil expenditures
Variables used in regression analysis of graduation outcomes	9th grade cohort year, Race, gender, 504 status, special education status, number of times student data was loaded into EWS in school year	School enrollment, share female, share of each racial/ethnic group, share FRPL, Title I, number of times school loaded any data into EWs in school year	

Appendix A2: Interview Protocol

1) (All participants) What is your role in the school/district?

2) How many years has your school/district (tailor to role) participated in the EWS?

How frequently does your school upload data to the EWS? Do you upload student data for certain students and not others?

a. If few engagements, ask the following questions:
   i. Has your school/district ever used the EWS beyond testing purposes?
   ii. What was your experience with the upload process of the Early Warning System?
   iii. What attracted you to the Early Warning System? What goals did you seek to accomplish? Did the EWS help or hinder the fulfillment of those goals?
   iv. What is the size of your school? Approximately what percent of the students did you add their information to the EWS?
   v. Was school size a factor in the choice of the EWS? Do you feel you know your students well enough that you do not need the EWS?
   vi. Approximately, what percentage of your students did you add their information to the EWS? What is the alternative to using an EWS?
   vii. What made you choose certain students over others?
   viii. Did you achieve your goals? Did you find different tools to use with your at-risk students?
   ix. What kind of interventions do you use with your at-risk students? Would they change if you had a better way to identify those students?
   x. What do you use to track your at-risk students for interventions, grants, etc.?

3) How many people review the EWS reports at your school/district?

   a. What are their roles?
   b. What is the dissemination process for EWS data?
   c. Do counselors and teachers have access to the data?

4) What does your EWS report review process look like? Is it formal and occurring at regular intervals? Is it incorporated with other data and intervention efforts or processes?

5) Are you responsible for uploading EWS data to OPI?

6) If so, do you have any comments as to the process?

7) Does the OPI provide your school/district with adequate training and support for the EWS?

8) In what ways do you receive the EWS data?

9) There are three reports in the EWS system. What is your opinion about the layout and information provided?

10) How accurate do you find these reports? Are you able to identify students that you suspect to be at-risk? Describe this process.

11) Are you able to identify students that you are unsure if they are at risk? Describe this process. Do you identify students differently if they are at risk or extreme at risk? How does this difference change the selected intervention?

12) Were you able to identify at risk students that the EWS missed?

13) What is the most beneficial aspect of EWS data?

14) What is the least beneficial aspect of EWS data?

15) What interventions does your school/district use if an EWS student is determined to be at risk or extreme at risk?

16) What do you think of the recommendations on the EWS summary report?

17) Following an intervention, have you used EWS data to track a student's outcome?

18) From your perspective, have your EWS interventions been effective?

19) What percentage of the interventions are successful, i.e., an identified at-risk student who receives some intervention, then graduates or goes on to the next grade?

20) What is the approximate cost per student of an intervention? Does this process cost less if you have a way to identify at risk/extreme at-risk students?

21) What could the OPI do to improve the EWS?

Appendix A3: Montana EWS Implementation Survey
Consent Form for Human Subjects Research at the Montana Office of Public Instruction

You are invited to participate in an Office of Public Instruction research study: Evaluation of a Predictive Model- Montana's Early Warning System for Dropouts.

You are invited to participate since your school/school district has used the EWS Model. The EWS initiative provides a profile for your Grades 3-12 students. In that profile we offer predictive modeling about the risk of dropping out. This research study evaluates the effectiveness of the program in three ways. We do tests to see if the model also predicts graduation and what is the impact of the program on subgroups. We also look to see how much the program is being used in your schools and if results lead to interventions that help students graduate. You are under no requirement to complete this survey. Participation is voluntary. You may answer some questions and not others or even stop the survey at any time. There are no known risks in completing this survey. The benefits to participating in the study is that we'll have a better understanding of the effectiveness of the Early Warning System and in turn encourage the use of the program to a broader audience. Our goal is for you to better identify potential dropouts in your school/school district. Your survey results will be kept confidential to the greatest degree allowed by the technology being used (Qualtrics). All responses will be reported in aggregate. We will not ask for name or any identifying information. We will ask for school/school district and role.

If you wish not to answer these questions that is your choice. This study is sponsored by the National Center for Education Research, a research arm of the US Department of Education. There is no cost to participate in the study.

Do you consent to participate in the study?

○ Yes (1)

○ No (2)

---

2 What is your role in the district?

○ Superintendent (1)

○ Curriculum Director (2)

○ School Leader (3)

○ School Counselor (4)

○ Other (please describe) (5) ____________________

---

3 How many years has your district participated in the EWS?

○ Less than 2 years (1)

○ Between 2 and 4 years (2)

○ 5 to 6 years (3)

- ○ More than 6 years (4)

4 Who in the district oversees uploading the data?

- ○ Superintendent (1)
- ○ Curriculum Director (2)
- ○ School Leader (3)
- ○ School Counselor (4)
- ○ Other (please describe) (5) ____

5 How many users have access to the data?

- ○ 1 (1)
- ○ Between 2 and 4 (2)
- ○ 5 to 6 (3)
- ○ More than 6 (4)

6 How many people are knowledgeable of the data and use it in different formats, for example, someone who prints out copies for other to use?

- ○ 1 (1)
- ○ Between 2 and 4 (2)
- ○ 5 to 6 (3)
- ○ More than 6 (4)

7 What is the size of your district

- ○ Less than 100 students (1)
- ○ Between 100 and 500 students (2)
- ○ Between 501 and 1000 students (3)
- ○ Greater than 1000 students (4)

8 Data has been uploaded in the district for how many students?

- ○ Less than 100 students (1)

- ○ Between 100 and 500 students (2)
- ○ Between 501 and 1000 students (3)
- ○ Greater than 1000 students (4)

9 How does your team use the EWS reports once you have information about students who are at risk?

____

10 Do you have a formal process to implement interventions based on the EWS?

- ○ Formal, all stakeholders review data before intervention (1)
- ○ Semi Formal, at least one stakeholder reviews data prior to intervention (2)
- ○ No Formal, EWS data is sometimes used as a reference (3)
- ○ Other (please describe) (4) ____

11 Of the students identified by the EWS at 'at risk' or 'high risk,' what percentage receive some kind of support or targeted intervention?

- ○ None (1)
- ○ Less than 25% (2)
- ○ Between 26% and 50% (3)
- ○ Between 51% and 75% (4)
- ○ Greater than 76% (5)
- ○ All (6)

12 What percentage of students that are not identified as at risk receive support or targeted intervention based on trends shown in the EWS data?

- ○ None (1)
- ○ Less than 25% (2)
- ○ Between 26% and 50% (3)
- ○ Between 51% and 75% (4)
- ○ Greater than 76% (5)
- ○ All (6)

13 What is the percentage of interventions with your at-risk students that are made using EWS data?

- ○ None (1)
- ○ Less than 25% (2)
- ○ Between 26% and 50% (3)
- ○ Between 51% and 75% (4)
- ○ Greater than 76% (5)
- ○ All (6)

14 What is the average number of times an administrator or counselor intervened with a particular student identified as at risk?

____

15 Do you have a process to follow up with students who receive an intervention? If yes, please describe

- ○ Yes, please describe (1) ____
- ○ No (2)

16 What percentage of students that receive an EWS informed intervention go on to the next grade or graduate?

- ○ None (1)
- ○ Less than 25% (2)
- ○ Between 26% and 50% (3)
- ○ Between 51% and 75% (4)
- ○ Greater than 76% (5)
- ○ All (6)

17 How helpful are the intervention suggestions in the EWS reports?

- ○ Helpful (1)
- ○ Not Helpful (2)
- ○ Not Sure/No opinion (3)