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Making an Impact

Getting students on track for graduation: Impacts of the Early Warning Intervention and Monitoring System after one year

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Key findings

This study examined the impact of the Early Warning Intervention and Monitoring System (EWIMS), a systematic approach to the early identification of and intervention with students at risk of not graduating from high school on time. The study randomly assigned 73 schools to use EWIMS or to continue with their usual practices for supporting at-risk students. After a year of limited implementation, the study findings show that:

- EWIMS reduced chronic absence and course failure but not the percentage of students with low grade point averages or suspensions.
- EWIMS did not have a detectable impact on student progress in school (credits earned) or on school data culture—the ways in which schools use data to make decisions and identify students in need of additional support.

The findings provide initial rigorous evidence that EWIMS is a promising strategy for reducing rates of chronic absence and course failure, two key indicators that students are off track for graduation. It is not clear what staff actions caused these improvements. EWIMS was challenging to implement in the first year and did not have an impact on other measured outcomes.

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This report is available on the Regional Educational Laboratory website at http://ies.ed.gov/ncee/edlabs.

Summary

Although high school graduation rates are rising—the national rate was 82 percent during the 2013/14 school year (U.S. Department of Education, 2015)—dropping out remains a persistent problem in the Midwest and nationally. Many schools now use early warning systems to identify students who are at risk of not graduating, with the goal of intervening early to help students get back on track for on-time graduation. Although research has guided decisions about the types of data and indicators used to flag students as being at risk, little is known about the impact of early warning systems on students and schools—and in particular, whether these systems do help get students back on track. This study, designed in collaboration with the REL Midwest Dropout Prevention Research Alliance, examined the impact and implementation of one early warning system—the Early Warning Intervention and Monitoring System (EWIMS)—on student and school outcomes.

EWIMS is a systematic approach to using data to identify students who are at risk of not graduating on time, assign students flagged as at risk to interventions, and monitor at-risk students' response to intervention. The EWIMS model provides schools with guidance to implement a seven-step process, supported by the use of an early warning data tool. The tool uses validated indicators, based on prior research, to flag students who are at risk of not graduating on time (Heppen & Therriault, 2008; Therriault, Heppen, O'Cummings, Fryer, & Johnson, 2010) and allows schools to assign students to interventions and monitor their progress. The indicators used to flag at-risk students in the tool are chronic absence (missed 10 percent of instructional time or more), course performance (failed any course, grade point average [GPA] below 2.0), behavioral problems (suspended once or more), and an off-track indicator (failed two or more semester-long or three or more trimester-long core courses or accumulated fewer credits than required for promotion to the next grade).[1] The EWIMS model is intended to help schools efficiently use data to identify at-risk students and provide targeted supports.

To assess the impact of EWIMS on student and school outcomes, 73 high schools in three Midwest Region states were randomly assigned to implement EWIMS during the 2014/15 school year (37 EWIMS schools) or to continue their usual practices for identifying and supporting students at risk of not graduating on time and to delay implementation of EWIMS until the following school year (36 control schools). The study included 37,671 students in their first or second year of high school, with 18,634 students in EWIMS schools and 19,037 students in control schools. EWIMS and control schools and students were similar on all background characteristics prior to random assignment.

The study examined the impacts of EWIMS on indicators of student risk and on student progress in school after the first year of EWIMS adoption.

The study found that EWIMS reduced the percentage of students with risk indicators related to chronic absence and course failure but not related to low GPAs or suspension:

- The percentage of students who were chronically absent (missed 10 percent or more of instructional time) was lower in EWIMS schools (10 percent) than in control schools (14 percent); this 4 percentage point difference was statistically significant.
- The percentage of students who failed one or more courses was lower in EWIMS schools (21 percent) than in control schools (26 percent); this 5 percentage point difference was statistically significant.

- The percentage of students who had a low GPA (2.0 or lower) was 17 percent in EWIMS schools and 19 percent in control schools; this difference was not statistically significant. However, sensitivity analyses that used continuous GPA data instead of the binary risk indicator showed that, on average, GPAs were higher in EWIMS schools (2.98) than in control schools (2.87); this difference was statistically significant.
- The percentage of students who were suspended once or more was 9 percent in both EWIMS and control schools; there was no statistically significant difference.

  EWIMS did not have an impact on student progress in school. That is, there was not a statistically significant difference between EWIMS and control schools in the percentage of students who earned insufficient credits to be on track to graduate within four years (14 percent in both).

At the school level, EWIMS did not have a detectable impact on school data culture, that is, the ways in which schools use data to make decisions and identify students in need of additional support.

In nearly all participating schools, overall implementation of the EWIMS seven-step process was low, and implementation was challenging. Nevertheless, EWIMS schools were more likely than control schools to report using an early warning system and having a dedicated team to identify and support at-risk students, but EWIMS schools did not differ from control schools in the frequency of data review or the number and type of interventions offered.

This report provides rigorous initial evidence that even with limited implementation during the first year of adoption, using a comprehensive early warning system can reduce the percentage of students who are chronically absent or who fail one or more courses. These short-term results are promising because chronic absence and course failure in grades 9 and 10 are two key indicators that students are off track for on-time graduation. However, because the past research linking indicators to on-time graduation is correlational, it is not yet known if improving these indicators leads to improving on-time graduation rates. Also, EWIMS did not have a detectable impact on other measured indicators that are related to students' likelihood of on-time graduation, including low GPAs, suspensions, and earning insufficient credits.

Future research is needed to better understand the mechanisms through which EWIMS had an impact on chronic absence and course failure and why EWIMS did not affect other outcomes. In particular, studies could focus on identifying which staff actions and student experiences lead to improved student outcomes. Studies should also examine whether schools achieve improved overall implementation in subsequent years and whether (and how) the observed impacts fade, grow larger, or extend to other risk indicators (low GPAs and suspensions); to intermediate outcomes (including student persistence and progress in school); and to long-term outcomes (including dropout and on-time graduation rates).

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Why this study?

The national high school on-time graduation rate reached its highest level in U.S. history—82 percent—during the 2013/14 school year (U.S. Department of Education, 2015). Even so, nearly one in five students did not graduate from high school, and graduation rates were lower for historically disadvantaged students. The most recent national graduation statistics also show that 73 percent of Black students and 76 percent of Hispanic students graduated from high school, compared with 87 percent of their White peers (U.S. Department of Education, 2015). Additionally, 75 percent of students from low-income families graduated in four years, as did 63 percent of English learner students and 63 percent of students in special education (U.S. Department of Education, 2015). The graduation rate was lower for male students (78 percent) than for female students (85 percent; Stetser & Stillwell, 2014).[2]

One strategy for improving graduation rates is early warning systems, which use research-based warning signs to identify students at risk of not graduating

The consequences of not graduating from high school are severe. When compared with graduating peers, students who drop out of school are more likely to be unemployed or underemployed, live in poverty, have poor health, and become involved in criminal activities (Belfield & Levin, 2007; Christle, Jolivette, & Nelson, 2007; Hayes, Nelson, Tabin, Pearson, & Worthy, 2002), suggesting that increasing on-time graduation rates would benefit both individuals and society.

States, districts, and schools are increasingly interested in using early warning systems to identify students who are at risk of not graduating on time and get them back on track

Early warning systems have emerged as one strategy for improving graduation rates. Such systems use research-based warning signs to identify students at risk of not graduating.[3] These warning signs can include indicators of engagement (for example, attendance), behavior (for example, suspensions), and course performance (for example, grades and credits) during middle and high school (Allensworth & Easton, 2005, 2007; Balfanz, Herzog, & Mac Iver, 2007; Neild & Balfanz, 2006; Silver, Saunders, & Zarate, 2008). More robust, comprehensive early warning systems also emphasize matching and assigning identified students to interventions to help them get on track for on-time graduation (Heppen & Therriault, 2008; Kennelly & Monrad, 2007; Jerald, 2006; Neild, Balfanz, & Herzog, 2007; Pinkus, 2008), as well as monitoring students' progress in these interventions (O'Cummings, Heppen, Therriault, Johnson, & Fryer, 2010; O'Cummings, Therriault, Heppen, Yerhot, & Hauenstein, 2011).

Educators have become increasingly interested in using early warning systems to identify students who are at risk of dropping out of school (Heppen & Therriault, 2008; Kennelly & Monrad, 2007; Neild et al., 2007). However, despite widespread implementation, there is little rigorous evidence of the impact of early warning systems on outcomes such as chronic absence, course failure, suspensions, progress in school, and, ultimately, on-time graduation. One recent experimental study tested the impact of Diplomas Now, a comprehensive school reform strategy with more targeted interventions for students who display early warning signs, on indicators related to attendance, behavior, and course performance (Corrin, Sepanik, Rose, & Shane, 2016). The study, which focused on students in grades 6 and 9, found that Diplomas Now had a positive and statistically significant impact on the percentage of students not flagged on any indicator but did not have a significant impact on average attendance, discipline, or course passing rates in either grade. Even with this new evidence of the limited impact of one type of early warning system on student indicators of risk, there is not much information on the impact of adopting other early warning indicator models on student outcomes or school outcomes, including data culture.[4]

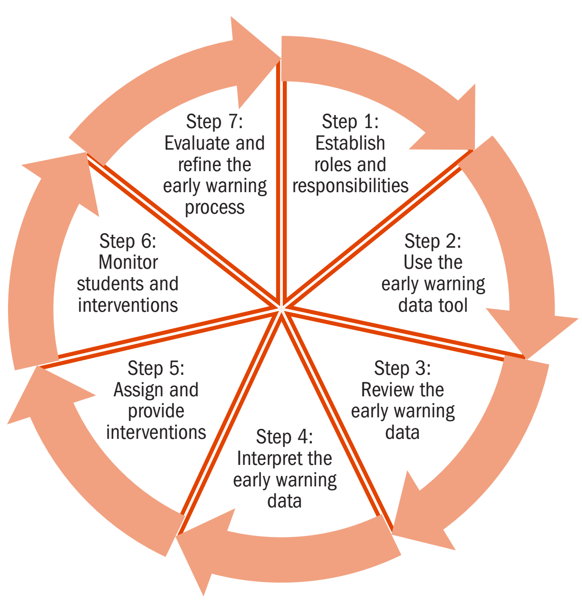
Members of the Midwest Dropout Prevention Research Alliance sought evidence of the impact of early warning systems on students and schools as a means to justify the costs associated with implementing them. To produce this evidence, the Regional Educational Laboratory (REL) Midwest and the Alliance collaborated on an experimental study of the impact of the Early Warning Intervention and Monitoring System (EWIMS) in 73 high schools across three states. The intended audience for this report includes alliance members, practitioners, policymakers, researchers, and education decisionmakers considering investing in an early warning system like EWIMS.

The Early Warning Intervention and Monitoring System is a systematic approach to reliably identifying students at risk of not graduating on time, assigning them to interventions, and monitoring their progress

EWIMS is a systematic approach to identifying students at risk of not graduating on time, assigning them to interventions, and monitoring their progress, with the goal of getting at-risk students back on track for on-time graduation

EWIMS was developed by the U.S. Department of Education–funded National High School Center at American Institutes for Research. EWIMS is a systematic approach to identifying students at risk of not graduating on time, assigning them to interventions, and monitoring their progress, with the goal of getting at-risk students back on track for on-time graduation. Schools implementing EWIMS receive guidance and site-based support to implement a seven-step process, which includes use of an early warning data tool (figure 1 and box 1). Typical implementation of EWIMS includes on-site and virtual support from technical assistance staff, some of whom are former educators or researchers in dropout prevention strategies. Appendix A includes more information about the technical assistance liaisons and the implementation support they provided to EWIMS schools in this study.

Figure 1. The Early Warning Intervention and Monitoring System seven-step implementation process



Source: Early Warning Intervention and Monitoring System (EWIMS) Implementation Guide. For more information about EWIMS implementation, see http://www.earlywarningsystems.org/wp-content/uploads/documents/EWSHSImplementationguide2013.pdf or Therriault et al. (2010).

Box 1. Early Warning Intervention and Monitoring System seven-step process and team

The seven-step EWIMS process guides educators to use data to identify students who show warning signs of falling off track toward on-time graduation and to monitor students' progress (see figure 1). Typical implementation of the model prioritizes identifying off-track students early in high school. The EWIMS steps are intended to be cyclical.

Step 1—Establish roles and responsibilities. Schools establish a team to lead and carry out the EWIMS process, determine the frequency and duration of meetings, and develop a shared vision for the team's work. The EWIMS team may be newly established or may build on or be integrated into an existing team (for example, a school improvement team, response to intervention team, or student support team). According to the EWIMS model, the team should include a broad representation of staff within the school and, ideally, the district (for example, principals, teachers, district administrators, and counselors), and EWIMS activities should be a priority of the team. Because EWIMS implementation is aligned with the academic calendar, the EWIMS team is expected to meet monthly and examine students' risk status and progress in interventions at the end of each grading period and at the end of the school year.

Step 2—Use the early warning data tool. The EWIMS team, with support from data or technology specialists, imports student demographic data and initial data on absences, course failure, grade point average, and behavior indicators into the early warning data tool (see box 2); updates administrative data as appropriate over the course of the school year; imports a list of available interventions into the tool; and runs automated or customized lists and reports.

Step 3—Review the early warning data. The EWIMS team focuses its attention on student- and school-level data, based on the indicators available in the tool. Data are reviewed to identify students who are at risk for not graduating on time and to examine patterns in student engagement and academic performance within the school. This step is critical when using any type of early warning data, although the focus here is on using the "research-based" indicators and thresholds preloaded into the tool. Step 3 is revisited any time new data become available.

Step 4—Interpret the early warning data. The EWIMS team seeks out and brings in additional data (besides the indicators) to better understand the specific needs of individual students or groups of flagged students. Unlike step 3, which is focused on the risk indicators in the tool, this step focuses on the underlying causes that might lead students to be identified as at risk on one or more indicators, using additional formal data (for example, administrative records) and informal input (for example, from teachers, family, and students).

Step 5—Assign and provide interventions. EWIMS team members make decisions about matching individual students to specific interventions in the school, district, and community, which are locally determined.

Step 6—Monitor students and interventions. The EWIMS team examines the student risk indicators on an ongoing basis to monitor the progress of students who have already been assigned to interventions. If these students continue to be flagged as at risk, the EWIMS team may consider assigning them to different interventions; if some of these students are no longer at risk, the team may consider ramping down services. In the long term, schools also may alter their catalog of interventions based on their effectiveness (adding new interventions and dropping those that do not help students get back on track). This step provides critical ongoing feedback about additional student- and school-level needs and apparent successes.

Step 7—Evaluate and refine the early warning process. Through active and structured reflection, EWIMS team members revise specific strategies or their general approach as needed and determine how best to allocate resources to support at-risk students. This step encourages EWIMS teams to make course corrections to any aspect of EWIMS implementation. As illustrated by the cyclical depiction of the seven-step process, this step (as well as the other six) reflects an ongoing process of continuous improvement.

Box 2. The early warning data tool

The EWIMS model includes an early warning data tool that enables schools to routinely examine indicators of whether students are "off track" and take action, if warranted. Schools first import student-level data, a course catalog, and a list of all interventions available to students. The tool then automatically flags students as at risk using thresholds based on prior research (see Heppen & Therriault, 2008; Therriault et al., 2010). The indicators include the following:[1]

- *Chronic absence flag.* Missing 10 percent or more of instructional time (one flag for the first 20 or 30 days, one flag per grading period, and a cumulative flag for the year).
- *Course failure flag.* Failed one or more semester-long or trimester-long courses in any subject (one flag per grading period and a cumulative flag for the year).
- *Low grade point average flag.* Earned a 2.0 or lower on a 4.0 scale or the equivalent on a different scale (one flag per grading period and a cumulative flag for the year).
- *Behavior flag.* Suspended once or more, or flagged according to some other locally validated definition (one flag per grading period and a cumulative flag for the year).
- *"Off track" flag.* Failed two or more semester-long or three or more trimester-long core courses (math, science, English, and social studies) or accumulated fewer credits than required for promotion to the next grade (one cumulative flag for the year). The "off track" flag definition is based on Allensworth and Easton's (2005; 2007) work on the "on-track" indicator.

The tool allows schools to customize settings (for example, by creating their own flag for students who failed grade 9 algebra), group students in various ways, and produce reports (including individual and student- and school-level data summaries) to guide dropout prevention strategies. The tool also allows and encourages users to record the assignment of flagged students to available interventions and monitor students' response to those interventions.

Note

1. The early warning data tool also includes an "incoming risk" flag, but schools in the study did not use it systematically. See appendix A for more detail on the incoming risk flag and how it was used in this study.

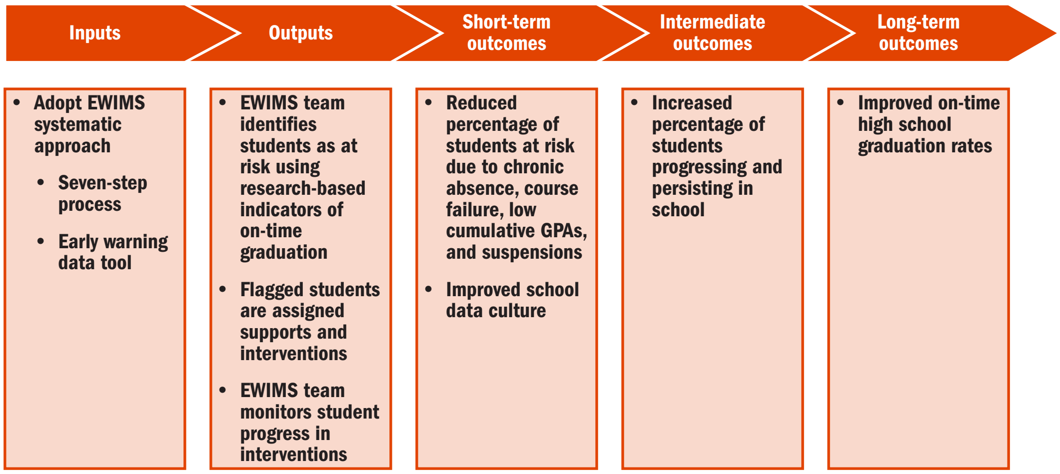
The early warning data tool flags students at risk using indicators drawn from prior research on the strongest predictors of on-time graduation. The tool allows schools to assign students to interventions and monitor their progress through multiple reporting features

The early warning data tool flags students at risk using indicators drawn from prior research on the strongest predictors of on-time graduation (see Heppen & Therriault, 2008; Therriault et al., 2010; box 2). In addition to flagging at-risk students, the tool allows schools to assign students to interventions and monitor their progress through multiple reporting features. The EWIMS model is intended to systematically and continually improve the ways that schools use data to identify at-risk students and efficiently and effectively provide targeted supports. EWIMS does not prescribe specific interventions; instead, it encourages schools to inventory their available interventions and consider (as part of the seven-step process) which are best suited to address at-risk students' needs.

The Early Warning Intervention and Monitoring System is expected to improve student- and school-level outcomes

The theoretical framework describes how EWIMS is expected to improve student and school outcomes (figure 2). EWIMS is intended to focus and streamline the data review process by using research-based early warning indicators to flag students who may be at risk of not graduating on time. This, it is assumed, will allow schools to more systematically identify students who need support. A dedicated team to identify and support at-risk

Figure 2. Theory of action for how the Early Warning Intervention and Monitoring System improves student and school outcomes



EWIMS is the Early Warning Intervention and Monitoring System.

Source: Authors' elaboration of the theory of action.

The effectiveness of EWIMS for students generally depends on the quality and appropriateness of the support provided

students (the EWIMS team) can then use this information to better align the type of support to specific students' needs. The effectiveness of EWIMS for students, therefore, depends on the quality and appropriateness of the support provided.

The use of EWIMS is expected to have short-term impacts on both schools and students. At the school level, EWIMS implementation is expected to change how schools use data to identify and support at-risk students, leading to improvements in some aspects of school data culture: for example, improvements in the context for data use (for example, goals and professional climate for data use), concrete supports for data use (for example, allocated time for using data or professional development on data use), data-driven student support (for example, data-based decisions about how to best target limited supports for students), and reduced barriers to data use (for example, lack of time to review data). Other aspects of school data culture (for example, professional climate for data use) may require several years to show improvement.

At the student level, EWIMS implementation should result in short-term reductions in the prevalence of students being flagged by indicators related to chronic absence (missing 10 percent or more instructional time), course failure (one or more course failures, GPAs of 2.0 or lower), and behavioral problems (for example, suspensions). These short-term reductions are then expected to lead to improved intermediate outcomes, including improvements in students' progress in school (by earning sufficient credits to remain on track toward on-time graduation) and persistence in school (by remaining continuously enrolled). Over the long term, EWIMS schools should see improved on-time graduation rates as a result of improvements in students' progress and persistence.

What the study examined

Together, the REL Midwest and the Dropout Prevention Alliance collaborated to design and conduct a randomized controlled trial to examine the early impact of EWIMS on student and school outcomes. The study examined the following research questions about the impact of EWIMS a year after its adoption:

1. What is the impact of EWIMS on indicators of student risk?
2. What is the impact of EWIMS on student progress in school?

The indicators of student risk were binary, meaning that they indicate whether students were above or below the thresholds used as the default settings in the early warning data tool; specifically, whether they missed 10 percent or more of instructional time, failed one or more courses, had GPAs of 2.0 or lower, and had one or more suspensions. Student progress was also binary: whether or not students had earned sufficient credits to be on track to graduate within four years (defined as earning one-fourth of the credits needed to graduate for first-year students and one-half of the credits needed to graduate for second-year students).

The study was a snapshot of early adoption of EWIMS and was not designed to examine implementation and student progress over multiple years

The study also examined whether the impact of EWIMS differed for first- and second-year students, because typical implementation of the model prioritizes identifying at-risk students as early in high school as possible (that is, the focus of early implementation is often on students in grade 9). In addition, the study posed an exploratory research question about the impact of EWIMS on school data culture, a key school-level outcome in the EWIMS theory of action. This question was considered exploratory because the study was not designed to detect significant impacts on school-level outcomes.

The study was a snapshot of early adoption of EWIMS and was not designed to examine implementation and student progress over multiple years. Therefore, persistence and dropout across school years and on-time graduation could not be examined but are critical outcomes for future research.

Four research questions about implementation were examined to provide context for understanding the impact of EWIMS on the main study outcomes:

1. To what extent did EWIMS schools participate in the professional development provided and implement the EWIMS seven-step process?
2. What barriers to implementation did EWIMS schools experience?
3. What types of interventions did EWIMS schools provide to students identified as at risk, and what percentage of students received those services?
4. To what extent did EWIMS and control schools differ in their practices for identifying and supporting students at risk of not graduating on time?

The study addressed these questions about EWIMS impact and implementation using a randomized controlled trial and quantitative and qualitative data. (Box 3 provides a summary of the data and methods used, and appendixes B and C provide more details.)

A total of 73 schools in three Midwest Region states participated in the study.[5] The schools were randomly assigned to either the treatment condition, with schools implementing EWIMS from spring 2014 through the end of the 2014/15 school year (37 EWIMS schools), or to the control condition (36 control schools). The control schools continued their usual practices for identifying and supporting students at risk of not graduating on time during the 2014/15 school year and were provided EWIMS in the following school year (2015/16). The study included 37,671 students in their first or second year of high school, with 18,634 students in EWIMS schools and 19,037 students in control schools (see table B3 in appendix B). First-year students were enrolled in grade 9 in the 2014/15 school year, and second-year students were enrolled in grade 9 in the previous (2013/14) school year. Differences between EWIMS schools and control schools were not statistically significant on any measured baseline characteristics (see table B5).

Box 3. Study design, data, and methods

Study design

This study used a randomized controlled trial to examine the impact of EWIMS on student and school outcomes. Schools were matched into pairs within states and districts based on school size, graduation rates, and initial dropout prevention efforts. Next, schools were randomly assigned within each pair to either implement EWIMS during the 2014/15 school year (37 EWIMS schools) or to continue their usual practices for identifying and supporting students at risk of not graduating on time and implement EWIMS in the following school year (36 control schools). See appendix B for details on the design, sample, and random assignment.

Data collection

The following data were collected for all schools (see appendix C for further details):

- Extant student records from the 2012/13 school year through spring 2015.
- School leader responses to a web-based survey administered in spring 2015 to measure school data culture and collect information about interventions used to support at-risk students. The survey was also administered in spring 2014 (after random assignment), but was used only as an additional data source to identify interventions available in EWIMS schools.

The following data were collected only for EWIMS schools (see appendix C for further details):

- Extant documents on EWIMS implementation during the 2014/15 school year.
- Monthly logs of the content and frequency of EWIMS team meetings during the 2014/15 school year.
- Reports from the early warning data tool that measured tool use through spring 2015.
- Interviews with EWIMS team members conducted in spring 2015.[1]

Measures

Student outcome measures. The student outcomes measures for the four risk indicators (missed 10 percent or more of instructional time, failed one or more courses, GPA of 2.0 or lower, and one or more suspensions) and for student progress in school were binary variables. Each binary variable was coded 1 or 0, reflecting whether the student was above or below the threshold for each risk indicator, or for progress in school, whether the student had earned sufficient credits to be on track to graduate within four years. See appendix C for operational definitions of each outcome.

School data culture measures. School data culture was measured with a set of survey items on the 2015 end-of-year school leader survey. These items yielded an overall score for data culture and subscores for four key dimensions: context for data use, concrete supports for data use, data-driven student support, and barriers to data use (table C3).

EWIMS implementation measures. Measures of school participation in each of the EWIMS professional development sessions—regional trainings, tool trainings, online trainings (called

(continued)

Box 3. Study design, data, and methods *(continued)*

WebShares), and school site visits—were based on attendance records indicating which school staff attended the sessions. Levels of implementation of the seven steps of the EWIMS process were generated using a rubric developed for the study. Measures of barriers to EWIMS implementation and specific types of interventions offered in EWIMS schools were extracted from extant records, surveys, and interviews and coded with key themes. Additional measures were used to assess the contrast between EWIMS schools and control schools in their practices for identifying and supporting at-risk students. These measures included the frequency of data review, the number and type of interventions, whether schools reported using an early warning system, and whether schools reported having a dedicated school-based team or group of individuals that reviews student data to support students identified as at risk of not graduating from high school. See appendix C for further detail.

Impact analysis

Multilevel logistic and linear regression models with students nested in schools were used to estimate the impact of EWIMS on student outcomes for the main research questions. Student-level covariates (level 1) and fixed effects for matched pairs (level 2) were included in these models to increase the precision of the estimate of the impact of EWIMS at both levels. Sensitivity analyses were conducted to determine if the impact of EWIMS was robust to different model specifications and whether the results were similar when the binary outcomes were replaced with their continuous counterparts. For example, low GPA (2.0 or lower) was replaced with GPA. See the "Impact analyses" section in appendix C for more information on the analytic approach and tables D1 and D2 in appendix D for sensitivity analysis findings.

Implementation analysis

To address implementation research questions, descriptive analyses of implementation data were conducted. Treatment contrast analyses used linear and logistic regression models with school covariates that tested whether or not EWIMS and control schools differed in their practices for identifying and supporting at-risk students. See appendix C, pages C-16–C-22, for more detail on the implementation analyses.

Note

1. Exit interviews were conducted with schools that chose to stop implementing EWIMS during the 2014/15 school year. See appendix C for further details on the interview and analytic approach; see appendix D for detailed findings.

Differences between EWIMS schools and control schools were not statistically significant on any measured baseline characteristics

What the study found

This section presents the main study findings for the impact of EWIMS on student and school outcomes and documents the implementation of EWIMS in study schools.

The Early Warning Intervention and Monitoring System reduced the percentage of students with risk indicators related to chronic absence or course failure but did not have a detectable effect on the percentage who had a low grade point average or were suspended

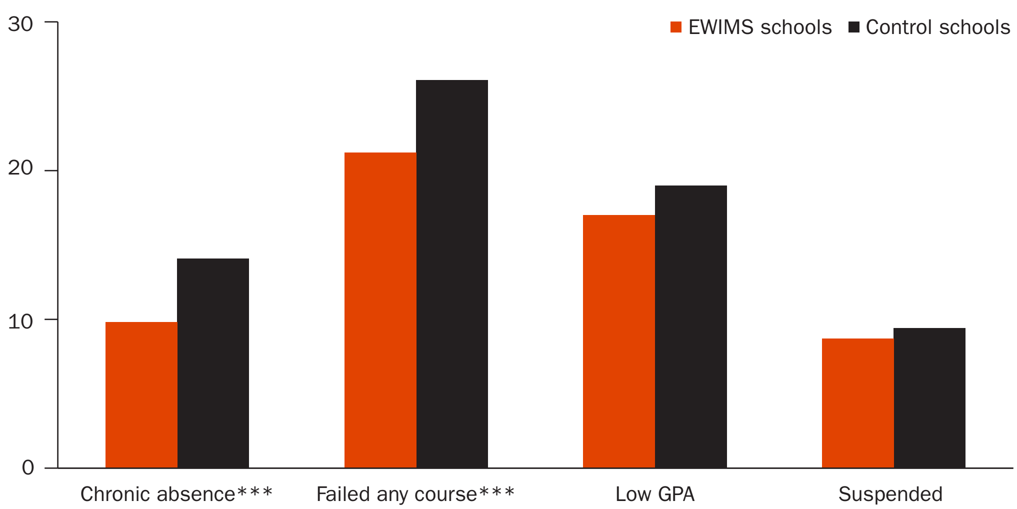
After one year of implementation, EWIMS reduced the percentage of students who were chronically absent or failed one or more courses but did not have an impact on the percentages of students who had a low GPA or were suspended (figure 3). Sensitivity analyses show that the findings reported here are robust and consistent across different analytic approaches (see tables D1 and D2 in appendix D).

Chronic absence. The percentage of students who were chronically absent (that is, missed 10 percent or more of instructional time) was lower in EWIMS schools (10 percent) than in control schools (14 percent; see figure 3). This 4 percentage point difference was statistically significant. The impact of EWIMS on chronic absence was larger for first-year students than for second-year students (see figure D1 and table D3 in appendix D). Sensitivity analyses that used continuous data on instructional time missed (instead of the binary risk indicator) showed that the average percentage of instructional time missed was statistically significantly lower in EWIMS schools (5.4 percent) than in control schools (6.5 percent; see table D2).

EWIMS reduced chronic absence and course failure but not the percentage of students with low grade point averages or suspensions

Course failure. The percentage of students who failed one or more courses was lower in EWIMS schools (21 percent) than in control schools (26 percent; see figure 3). This 5 percentage point difference was statistically significant. The impact of EWIMS on course failure was larger for first-year students than for second-year students (see figure D1 and table D3 in appendix D). Sensitivity analyses that used continuous data instead of the binary risk indicator showed that the average percentage of courses that students failed (out of the number of courses attempted) was also statistically significantly lower

Figure 3. The Early Warning Intervention and Monitoring System reduced the percentage of students with risk indicators related to chronic absence and course failure but not the percentage with indicators related to low GPA or suspensions in 2014/15



*** difference significant at $p < .001$.

EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: Model-adjusted percentage of students identified as at risk in EWIMS and control schools, controlling for school and student covariates, are presented. Higher values indicate a larger percentage of students at risk. Sample included 65 schools and 35,876 students for “chronic absence”; 65 schools and 35,133 students for “failed any course”; 57 schools and 30,080 students for “low GPA”; and 63 schools and 35,501 students for “suspended.” Note that less than 1 percent of the student analytic sample was dropped for chronic absence, low GPA, and suspended due to perfect prediction. Additional details about the models and samples used to generate these findings can be found in the notes to table D1 in appendix D.

Source: Authors’ analysis based on extant student records from schools, school districts, and state education agencies described in appendix C.

in EWIMS schools (8 percent) than in control schools (10 percent; see table D2). Also, the percentage of students who failed one or more core academic courses (English, math, science, and social studies) during the 2014/15 school year was lower in EWIMS schools (20 percent) than in control schools (24 percent)—a 4 percentage point difference that was statistically significant (see table D1).

Low grade point average. The percentage of students who had a GPA of 2.0 or lower was 17 percent in EWIMS schools and 19 percent in control schools (see figure 3). This difference was not statistically significant (see table D1 in appendix D). However, sensitivity analyses that used continuous GPA data instead of the binary risk indicator showed that, on average, GPAs were higher in EWIMS schools (2.98) than in control schools (2.87); this difference was statistically significant (see table D2).

Suspension. The percentage of students who were suspended once or more was 9 percent in both EWIMS and control schools, and the difference was not statistically significant (see figure 3, and table D1 in appendix D).[6]

The Early Warning Intervention and Monitoring System did not have a detectable impact on student progress in school or on school data culture

The Early Warning Intervention and Monitoring System did not have a detectable impact on student progress in school

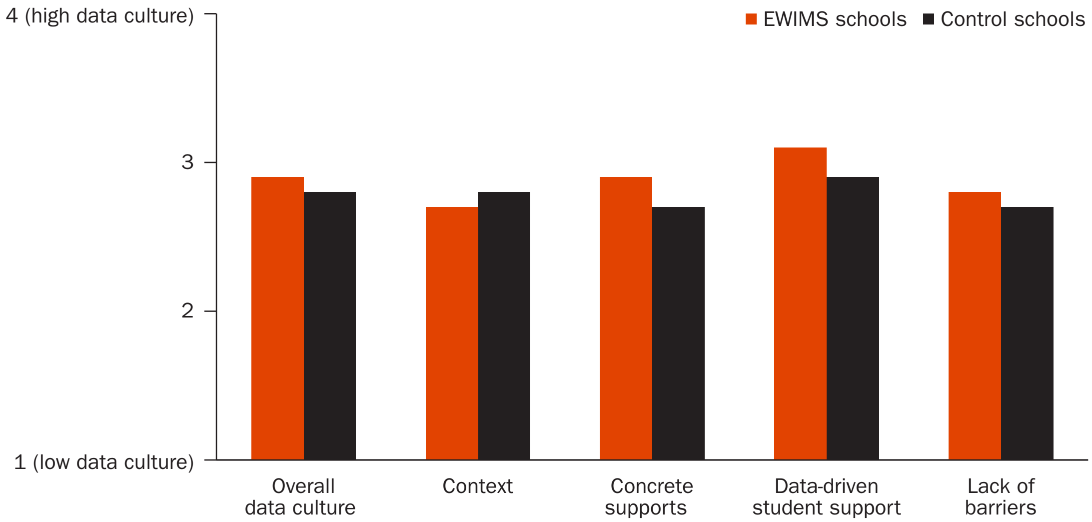
There was no statistically significant difference in the percentage of students who, by the end of the 2014/15 school year, had earned insufficient credits to be on track to graduate within four years. The percentage of students with insufficient credits was 14 percent in both EWIMS and control schools (see table D1 in appendix D). Sensitivity analyses that used continuous credits earned instead of the binary risk indicator were consistent; that is, there was no statistically significant difference in the average number of credits earned between EWIMS and control schools (students earned an average of 13 credits in both; see table D1).

As noted earlier, it was out of scope for this study to examine persistence or dropout across school years. However, analysis of a preliminary measure of persistence within the 2014/15 school year indicated that 95 percent of the students in both EWIMS and control schools were still enrolled at the end of the 2014/15 school year and the difference was not statistically significant. See appendix C and figure D2 and table D4 in appendix D for more detail about the measure and analysis of preliminary persistence.

The Early Warning Intervention and Monitoring System did not have a detectable impact on school data culture

EWIMS did not have a detectable impact on school data culture, as measured with the 2015 end-of-year survey of school leaders (figure 4). Differences between EWIMS schools and control schools on the overall data culture scale or any of its subscales, including context, concrete supports, barriers for data use, and data-driven student support, were not statistically significant (see table D5 in appendix D). However, the effect size (Hedges' *g*) for the overall school data culture scale was 0.27, suggesting that although not statistically significant, EWIMS schools reported modestly higher data culture than control schools (see table D5).[7] As noted earlier, analyses of school-level outcomes are considered exploratory because the study did not include a large enough number of schools to detect modest effects on school-level outcomes.

Figure 4. The Early Warning Intervention and Monitoring System did not have a detectable impact on school data culture at the end of the 2014/15 school year



EWIMS is the Early Warning Intervention and Monitoring System.

Note: Sample included 66 schools that completed the school leader survey items (32 EWIMS schools and 34 control schools) for overall data culture, concrete supports, data-driven student support, and lack of barriers. Sample included 67 schools that completed the school leader survey items (33 EWIMS schools and 34 control) for context. Data culture items were measured on a scale of 1 to 4, with 1 being low data culture and 4 being high data culture. The items that compose the scale for barriers to data use were reverse coded, such that a higher score indicated fewer barriers. The differences between the EWIMS and control schools in standard deviation units (Hedges' *g*, using a pooled standard deviation) were 0.27 for overall data culture, –0.02 for context, 0.22 for concrete supports, 0.31 for data-driven student support, and 0.19 for lack of barriers. Regression models that regressed data culture on treatment status, a set of three covariates (school size, baseline graduation rate, and baseline data-driven dropout prevention efforts), and a set of variables capturing school matched pairs revealed no statistically significant differences at the $p < .05$ level. Additional details about these findings can be found in table D5 in appendix D.

Source: Authors' analysis based on school leader survey administered in spring 2015.

For participating schools, the level of overall implementation of the Early Warning Intervention and Monitoring System seven-step process was low, and implementation was challenging

Despite the training and support that EWIMS schools received, the implementation findings suggest that schools found it difficult to implement the model in the first year of adoption

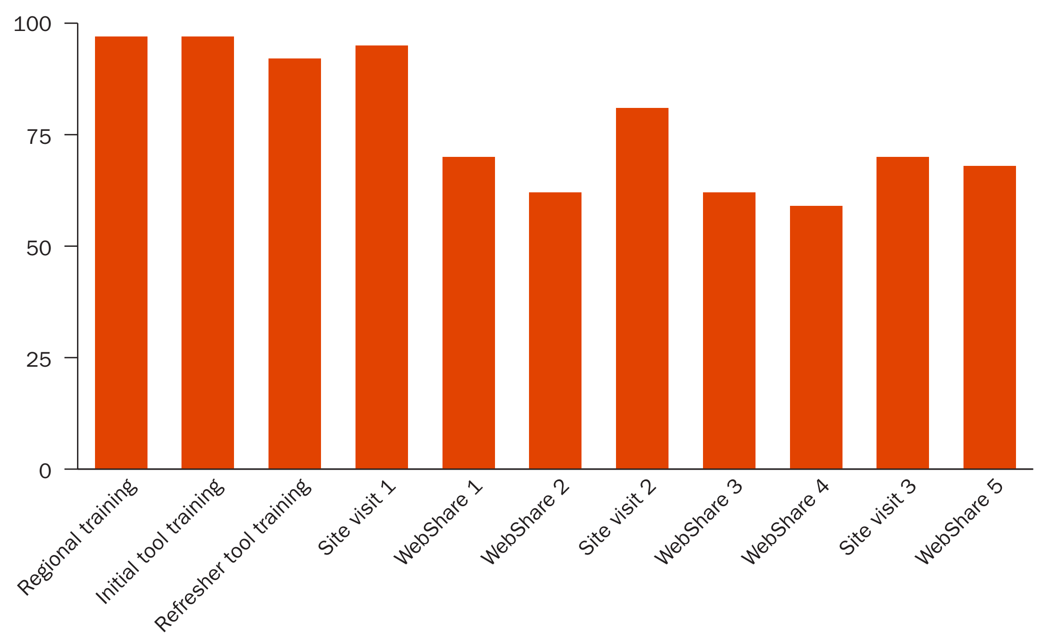
Despite the training and support that EWIMS schools received, the implementation findings suggest that schools found it difficult to implement the model in the first year of adoption. Approximately 80 percent of EWIMS schools implemented EWIMS as planned in the 2014/15 school year. Out of the full sample of 37 EWIMS schools, one never implemented EWIMS (and dropped out of the study after random assignment, but before EWIMS implementation began) and seven stopped implementing EWIMS during the 2014/15 school year.[8] The sections that follow summarize information on school participation in EWIMS training, levels of implementation for each of the seven steps and overall, barriers to implementation experienced by EWIMS schools, and the specific types of interventions offered in EWIMS schools and the percentage of students who received those services.

Participation in training on the early warning data tool and seven-step process was high among EWIMS schools at the start but declined during the 2014/15 school year. EWIMS implementation liaisons delivered a total of 11 trainings to EWIMS schools between April 2014 and June 2015. These included an individual school training on how to use the early warning data tool, regional training (for multiple EWIMS schools) on how to implement the seven-step process, a refresher tool training at the beginning of the 2014/15 school year, and ongoing follow-up throughout the 2014/15 school year (including school site visits, online trainings called WebShares, and responsive technical assistance using telephone and email on an as-needed basis). Participation in EWIMS trainings declined throughout the 2014/15 school year, from a high of 97 percent for the first regional training to a low of 59 percent for the fourth WebShare meeting (figure 5). However, throughout the 2014/15 school year, staff satisfaction with EWIMS trainings was high—more than 90 percent of respondents were either satisfied or very satisfied with each training (see table D6 in appendix D).

Only two schools achieved moderate or high levels of implementation across all seven steps in the 2014/15 school year. EWIMS schools were categorized as high, moderate, or low implementers of the full EWIMS model based on a combination of multiple key features per step (see table D7 in appendix D). This measure was developed to gauge full implementation of EWIMS across all seven steps at any point of implementation, not just in the first year of adoption. Because EWIMS is intended to be a process of continuous improvement across multiple years, achieving high ratings in the first year may be challenging for many schools. Higher levels of implementation might be expected in subsequent years as schools reflect on successes and challenges from their first year and make improvements. However, it is also possible that implementation levels might decline in subsequent years if schools lose interest or motivation to implement EWIMS; a longer study is needed to document implementation levels over time.

During the first full school year of implementation, all but two EWIMS schools were categorized as low implementers across all seven steps. However, many EWIMS schools had moderate or high implementation ratings for individual steps of the seven-step model

Figure 5. Participation in professional development sessions was highest for the initial trainings and decreased for site visits and WebShares during 2014/15



Note: The full Early Warning Intervention and Monitoring System (EWIMS) school sample includes 37 schools, one of which never implemented EWIMS (and dropped out of the study after random assignment, but before EWIMS implementation began) and seven of which stopped implementing EWIMS during the 2014/15 school year. Professional development sessions are presented in the order in which they were provided to EWIMS schools. A timeline of these activities can be found in table A1 in appendix A.

Source: Authors' calculations based on attendance sheets collected during each professional development session.

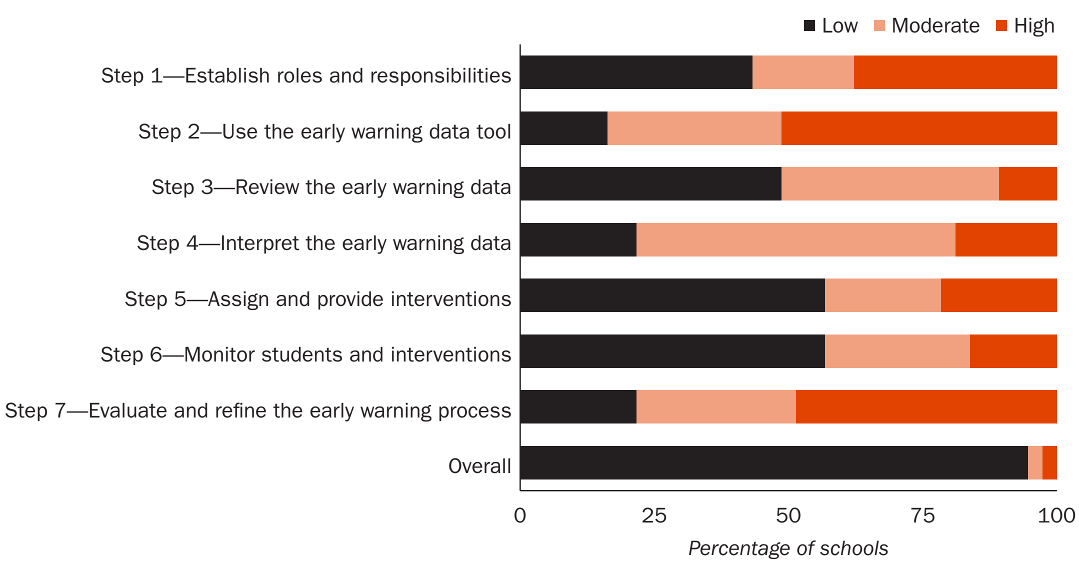
During the first full school year of implementation (2014/15), all but two EWIMS schools (95 percent) were categorized as low implementers.[9] Across all seven steps, one school achieved a moderate implementation rating and one achieved a high implementation rating. However, many EWIMS schools had moderate or high implementation ratings for individual steps of the seven-step model (11 percent to 51 percent; figure 6 and see table D7 in appendix D).

Twenty-six EWIMS schools (70 percent) achieved high ratings on at least one step of the EWIMS process, and eight schools (22 percent) achieved high ratings on at least four of the seven steps (see table D8 in appendix D). More than a third (38 percent) of EWIMS schools were coded as being high implementers of step 1 (establishing roles and responsibilities) and more than half (51 percent) as being high implementers of step 2 (using the early warning data tool). Steps 3–6—reviewing and interpreting EWIMS data, assigning and providing interventions to students, and monitoring students over time—appeared more challenging for most EWIMS schools to implement at high levels in the 2014/15 school year; only 11 percent to 22 percent achieved high levels of implementation of these steps. However, almost half (49 percent) of EWIMS schools had a high level of implementation of step 7 (evaluating and refining the EWIMS process), suggesting that even with limited overall implementation across the full process, schools reflected on how they used EWIMS and either made changes to meet their needs throughout the school year or planned future changes to EWIMS for the following school year.

Schools experienced barriers to implementation such as technical difficulties uploading student data into the early warning data tool and changes in staffing that affected the EWIMS team

Barriers experienced by schools implementing the Early Warning Intervention and Monitoring System in the 2014/15 school year included difficulty using the early warning data tool and staffing issues. Data from the school leader survey, interviews, and

Figure 6. Many Early Warning Intervention and Monitoring System schools achieved moderate and high implementation of individual steps during 2014/15



Note: The full Early Warning Intervention and Monitoring System (EWIMS) school sample included 37 schools, one of which never implemented EWIMS and dropped out of the study after random assignment but before intervention, and seven of which stopped implementing EWIMS during the 2014/15 school year. Additional details about the findings presented in this figure can be found in table D7 in appendix D.

Source: Authors' calculations based on school leader survey, early warning data tool reports, monthly meeting logs, and EWIMS team interviews.

documentation from the EWIMS technical assistance liaisons suggest that schools experienced notable barriers to implementing EWIMS in the 2014/15 school year. In particular, schools encountered difficulty importing data into the early warning data tool (24 schools, 65 percent), sometimes as a result of incompatibility with student information systems (6 schools, 16 percent), limited technical and data capacity of staff assigned to support tool use (5 schools, 14 percent), or limited personnel time to dedicate to importing data into the tool (13 schools, 35 percent). In addition, four schools (11 percent) experienced turnover of key staff, such as the principal or the individual responsible for preparing and importing data into the tool. Two schools (5 percent) preferred to use their own student information system to flag students at risk of not graduating on time (instead of the early warning data tool) but continued to implement the seven-step EWIMS process.[10] Implementation challenges appeared to be insurmountable for the eight schools that stopped or never began implementing EWIMS during the study (22 percent of the EWIMS school sample; see page D-8 in appendix D).

The most common types of interventions offered in EWIMS schools were academic supports; attendance and behavioral supports were less common

EWIMS schools offered a range of interventions to support at-risk students, but according to the data in their early warning data tools, less than 30 percent of the flagged students were assigned to interventions. Across all EWIMS schools with data in their early warning data tools, data for 19,309 students had been uploaded.[11] Of these students, 50 percent (9,559) were flagged on at least one risk indicator during the 2014/15 school year: 30 percent for chronic absence, 26 percent for failing one or more courses, 24 percent for a low GPA, and 6 percent for suspensions. About 12 percent of students were flagged for both chronic absence and course failures. More detail about how these samples differ from those in the primary impact models is shared in appendix D, page D-9.

A key step in implementing EWIMS is that schools assign students to interventions and monitor their progress over time. On average, data from the early warning data tools indicate that EWIMS schools assigned 27 percent of flagged students to at least one intervention in the 2014/15 school year (ranging from 0 to 67 percent within schools). Moreover, 22 percent of the 9,559 students identified as at risk in the early warning data tools were assigned to interventions aligned to their risk indicators (for example, students flagged for course failure were assigned to academic interventions). However, these analyses should be interpreted with caution because they rely on schools' use of the intervention features in the early warning data tool, and assignment to an intervention may have occurred outside of the tool.

The most common types of interventions offered in EWIMS schools were academic supports; attendance and behavioral supports were less common (see table D9 in appendix D). Interventions ranged from formal programs (such as online credit recovery for students who failed a course) to less formal strategies (such as meeting with a student or parents). Twenty-six of the 37 EWIMS schools (70 percent) offered at least one academic intervention to support at-risk students. For example, 38 percent of EWIMS schools offered targeted supports in English language arts, and 35 percent offered targeted supports in algebra. In addition, 68 percent of EWIMS schools offered tutoring to students, of which 19 percent offered peer tutoring. Nearly two-thirds of EWIMS schools (65 percent) offered credit recovery interventions, while a smaller subset of schools offered online credit recovery (27 percent). A majority of EWIMS schools (62 percent) offered mentoring programs. Fewer schools (30 percent) used peer mentors. Behavioral and attendance interventions were less common in EWIMS schools (24 percent of schools focused on attendance using truancy interventions, 16 percent had interventions that focused primarily on behavior through disciplinary actions, and 14 percent had dedicated social emotional interventions). Additional nonacademic support intervention strategies included conferences with students and parents (41 percent of schools), letters or phone calls home (38 percent), counseling (30 percent), student contracts (24 percent), and mental and physical health services (24 percent; see table D9 in appendix D).

Early Warning Intervention and Monitoring System schools were more likely than control schools to report using an early warning system and having a dedicated team to identify and support at-risk students but did not differ from control schools in the self-reported frequency of data review and number and type of interventions offered

To examine the contrast between EWIMS and control schools in their practices related to identifying and supporting at-risk students, the study used data from the spring 2015 school leader survey. To gauge the extent to which schools adhered to their randomly assigned groups, the survey asked school leaders whether they used an early warning system during the 2014/15 school year (see appendix C for the definition of early warning systems provided to school leaders during on-site or virtual presentations as part of the recruitment process for the study). Beyond self-reported use of an early warning system, the study also examined contrasts between EWIMS and control schools in some early warning system–related practices. These analyses included items asking schools whether they had a dedicated school-based team or group of individuals that reviewed student data to support students identified as at risk of not graduating from high school (hereafter referred to as a dedicated team to identify and support at-risk students), how often they reviewed attendance and course performance data, and how many and what types of interventions they offered to students.

To examine the contrast between EWIMS and control schools in their practices related to identifying and supporting at-risk students, the study used data from the spring 2015 school leader survey

The results suggest that EWIMS and control schools generally reported adhering to random assignment—most EWIMS schools reported using an early warning system and most control schools did not. Of the five measures used to assess contrasts in specific practices, EWIMS and control schools differed on one: having a dedicated team to identify and support at-risk students. On the other four measures, self-reported differences between EWIMS and control schools were not statistically significant. However, because the study was not designed to detect statistically significant differences on school-level measures, effect sizes for the magnitude of these differences are presented below.

Has an early warning system. Consistent with the random assignment groupings, many more EWIMS schools than control schools reported using an early warning system (figure 7). This difference was statistically significant and large in magnitude, translating to an effect size of 2.50 (see table D10 in appendix D).

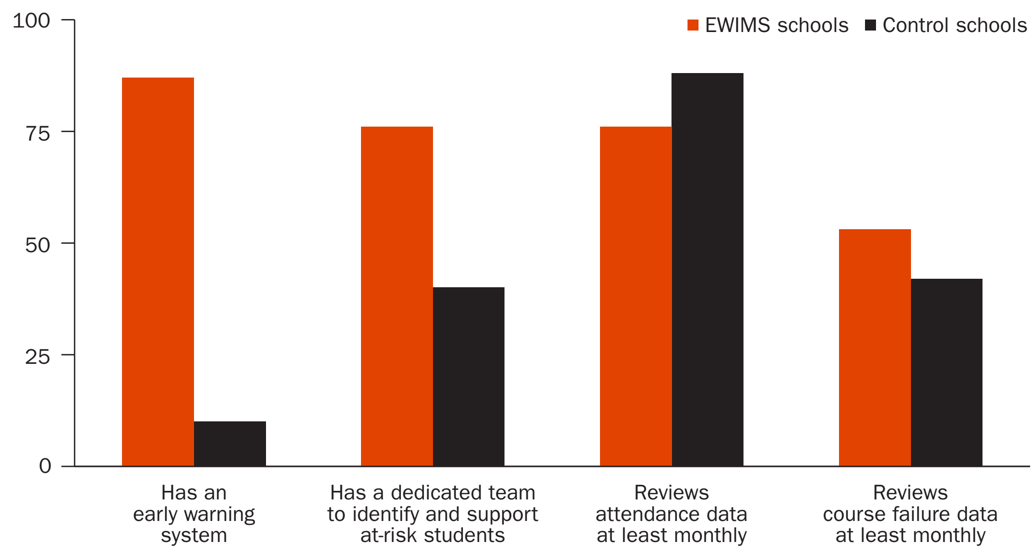
Has a dedicated team to identify and support at-risk students. More EWIMS schools than control schools reported having a dedicated team to identify and support at-risk students (see figure 7)—a key first step in the EWIMS seven-step process. This difference was statistically significant and large in magnitude, translating to an effect size of 0.95 (see table D10 in appendix D).

Frequency of data review. School leaders from nearly all EWIMS and control schools (91 percent in both) reported that their schools reviewed both attendance and course failure data to identify at-risk students during the 2014/15 school year (see table D11 in appendix D). Seventy-six percent of EWIMS schools reported that they reviewed attendance data at least monthly, compared with 88 percent of control schools (see figure 7). This difference was not statistically significant, although the effect associated with this difference was of notable size (–0.51), and favored control schools (see table D12). In contrast, 53 percent of EWIMS schools reported reviewing course failure data at least monthly, compared with 42 percent of control schools. This difference was not statistically significant, and the effect size was 0.25 (see figure 7 and table D12).

Number and type of interventions. There were no statistically significant differences between EWIMS and control schools in the number or type of interventions that school leaders reported they had available to support students. With respect to the number of interventions, EWIMS schools reported an average of 2.75 interventions and control schools reported an average of 2.20 interventions, a difference that translates to an effect size of 0.29 (see page D-12). With regard to types of interventions, few EWIMS or

Of the five measures used to assess contrasts in specific practices, EWIMS and control schools differed on one: having a dedicated team to identify and support at-risk students. On the other four measures, self-reported differences between EWIMS and control schools were not statistically significant

Figure 7. Early Warning Intervention and Monitoring System schools and control schools differed on some but not all self-reported early warning system–related practices during 2014/15



EWIMS is the Early Warning Intervention and Monitoring System.

Note: The school sample includes the 66 schools (32 EWIMS schools and 34 control schools) that completed the school leader survey for the items about data review and early warning systems and the 65 schools (31 EWIMS schools and 34 control schools) that completed the school leader survey for the item about the dedicated team to identify and support at-risk students. The five EWIMS schools that reported not using an early warning system were among the eight schools that had never started, or that stopped, implementing EWIMS in the 2014/15 school year. The four control schools that reported using an early warning system described those systems as involving behavior intervention monitoring and more informal systems, such as regular meetings among counselors and administrators. The item measuring whether or not a school has a dedicated team to identify and support at-risk students included an “other” response option; two EWIMS and four control schools responded with this response, indicating that the work was done by smaller teams or that schools were just putting the team together. Logistic regression models that regressed a binary indicator of whether or not a school had an early warning system, had a school-based team, reviewed attendance data monthly, or reviewed course failure data at least monthly on treatment status and a set of three covariates (school size, baseline graduation rate, and baseline data-driven dropout prevention efforts) revealed no statistically significant differences at the $p < 0.05$ level between EWIMS and control schools. Additional details about the findings presented in this figure can be found in tables D10 and D12 in appendix D.

Source: Authors’ calculations based on school leader survey.

control schools offered attendance or behavior interventions, but all control and nearly all EWIMS schools offered course performance (academic) interventions (see table D13 in appendix D).

Implications of the study findings

In 2008, the U.S. Department of Education's Dropout Prevention Practice Guide listed "using data systems as a diagnostic tool to understand dropout trends and identify individual students at risk of dropping out" as the first of six related recommendations (Dynarski et al., 2008). However, no rigorous evidence was available at the time to support this use of data systems. Nevertheless, schools, districts, and states across the country are increasingly using early warning systems to identify students at risk of not graduating on time. This study provided an initial large-scale, rigorous test of the use of this strategy, focusing specifically on the EWIMS model.

Despite low levels of implementation, the study found that EWIMS reduced the percentage of students who were flagged by risk indicators related to chronic absence and course failure; however, EWIMS did not have a detectable impact on the intermediate outcome of student progress in school

Despite low levels of implementation, the study found that EWIMS reduced the percentage of students who were flagged by risk indicators related to chronic absence and course failure. These short-term results are promising because chronic absence and course failure in grades 9 and 10 are two key predictors that students will not graduate on time (Allensworth & Easton, 2005, 2007; Balfanz et al., 2007; Heppen & Therriault, 2008; Neild & Balfanz, 2006). However, because the past research linking indicators to on-time graduation is correlational, it is not yet known if changing these indicators translates into an improvement in on-time graduation rates. Also, EWIMS did not have a detectable impact on other measured short-term indicators of risk that are also related to students' likelihood of on-time graduation, including suspensions and low GPAs (although it did increase average GPAs). In addition, EWIMS did not have a detectable impact on the intermediate outcome of student progress in school (as measured by the number of credits students had earned).

The mechanisms by which EWIMS reduced the percentage of students at risk due to chronic absence and course failure are unclear. In particular, it is not known which staff actions led to these impacts. The EWIMS theory of action proposes that impacts on students may occur as a result of changes in school data use. Although EWIMS implementation levels were low overall, the study found a difference between EWIMS and control schools in school data culture in the hypothesized direction, favoring EWIMS schools. However, the difference was not large enough to be statistically significant. Other school-level processes, unmeasured in this study, also may have contributed to impacts on students. For example, effects might have emerged for chronic absence and course failure if schools prioritized encouraging students to show up and participate in their courses, even if they did not have a sophisticated set of interventions. Further research is needed to better understand the mechanisms through which EWIMS had an impact on chronic absence and course failure.

Although EWIMS reduced the percentage of students with one or more course failures, there was no detectable impact on the related course performance indicator (a GPA of 2.0 or lower). Sensitivity analyses, however, which used continuous GPA data rather than a cutoff, showed a positive impact on average GPA. It is possible that in the first year of adoption, EWIMS may have had an impact on reducing course failure through modest improvements in course grades, so that at-risk students may have earned a D instead of an F in some of their courses, but not necessarily a C or better. Modest improvements in course grades would translate into reduced course failures and higher average GPAs, but would not have an impact on the percentage of students at risk due to a low GPA (2.0 or lower).

EWIMS also did not have an impact on the percentage of students who were suspended during the study year. This finding may be partially explained by a lack of variability and relatively low incidence of reported suspensions in EWIMS and control schools (on average, 9 percent in both); by measurement challenges associated with behavioral data, as described under Study Limitations below; or by the relative difficulty of intervening with students who have more serious disengagement issues with school.

EWIMS did not have an impact on progress in school (as measured by whether students had earned sufficient credits to be on track to graduate within four years), although it did reduce course failures. It is unclear why EWIMS did not have an impact on either earning insufficient credits or the average number of credits students earned, given that credit accrual is based on course performance.

Although EWIMS had no detectable impact on the course performance indicator (a GPA of 2.0 or lower), sensitivity analyses, which used continuous GPA data rather than a cutoff, showed a positive impact on average GPA

EWIMS was challenging for the study schools to implement. Initial participation in training on the early warning data tool and seven-step process was high among EWIMS schools during the summer, but participation declined during the 2014/15 school year. Only two schools achieved moderate or high levels of implementation across all seven steps in the 2014/15 school year. EWIMS schools reported a number of barriers to implementation, including challenges related to using the early warning data tool and staffing issues. These barriers seemed to be insurmountable for the eight schools that stopped or never began implementing EWIMS during the study (22 percent of EWIMS schools). The implementation challenges experienced by study schools are important for schools, districts, or states to consider when adopting EWIMS or another early warning system.

Despite low overall levels of implementation, EWIMS schools and control schools adhered to their randomly assigned group; many more EWIMS schools than control schools reported using an early warning system. In addition, more EWIMS schools than control schools reported having a dedicated team to identify and support at-risk students. All of the remaining treatment contrast analyses—the frequency of course failure data review and the number and type of interventions—favored EWIMS schools, with effect sizes typically above 0.25, even though the differences were not statistically significant. The one exception was that a larger share of control schools than EWIMS schools reported reviewing attendance data at least monthly. Impacts on student outcomes might have been greater had there been larger differences between EWIMS and control schools in practices for identifying and supporting at-risk students. Nevertheless, the study provides an unbiased estimate of the impact on study outcomes of EWIMS as it was implemented in the first year in 37 schools compared with business-as-usual practices in 36 control schools.

Future studies should examine whether schools achieve higher overall levels of implementation of EWIMS in subsequent years. Future research should also examine whether (and how) the impact of EWIMS on chronic absence and course failure in the short term fades, grows, or expands in subsequent years to other risk indicators (low GPAs and suspensions), to intermediate outcomes (including student persistence in school, student progress in school, and school data culture), or to long-term outcomes (including dropout and on-time graduation rates).

Limitations of the study

This study has a number of limitations that should be kept in mind. These limitations relate to a lack of information on longer term outcomes, the generalizability of the findings, a lack of detailed information on students in control schools, limited statistical power to detect school-level effects, and measurement issues.

- The findings in this report document the early impact of EWIMS, after just one year (14 months) of implementation in study schools and do not measure dropout or on-time graduation rates over multiple years. Future research should examine if and how EWIMS affects dropout and on-time graduation rates and document the effects of EWIMS after a longer period of implementation.
- The findings in this study may not be generalizable to other schools, given that the study sample consisted of schools in three REL Midwest Region states that were interested in implementing EWIMS and willing to participate in a random assignment study. The findings also may not generalize to schools with lower on-time graduation rates than the schools that participated in the study, including so-called "dropout factories," defined as schools in which the reported grade 12 enrollment is 60 percent or less than the grade 9 enrollment three years earlier (DePaoli et al., 2015). Three schools that participated in the study had very low on-time graduation rates (around 60 percent), but most were higher. The findings also may not generalize to other early warning systems, which vary in their comprehensiveness or the degree to which they articulate the implementation process.

Future research should document the effects of EWIMS after a longer period of implementation

- The indicators used to flag students as at risk of not graduating on time in the EWIMS tool were based on prior research and were not locally validated within participating districts and schools. It is possible that the results would be different with the use of locally validated thresholds and predictors of on-time graduation to identify at-risk students.
- Fourth, the study did not collect detailed information about how control schools used data and interventions to support at-risk students. Asking control schools to document this information was problematic because tracking this information resembles a key ingredient of EWIMS. For control schools to collect these data may have diminished the contrast between EWIMS and control schools that was important to providing a fair test of the EWIMS model. Therefore, only school-level data in control schools were collected through web-based surveys of school leaders. More detailed data from control schools would clarify the contrast between the two groups of schools in their early warning indicator–related practices during the year of the study.
- The school-level analyses had limited statistical power; therefore, findings based on the survey of participating schools are considered exploratory and should be interpreted with caution.
- Measures of student GPA and progress in school (based on the number of credits earned) may have underestimated the impact of EWIMS because for second-year students these measures included course failure and credits from the first year of high school, prior to full implementation of EWIMS. This limitation does not apply to first-year students.
- The impact of EWIMS on reducing the number of suspensions may not be detectable due to measurement challenges posed by school discipline data. Although there is no reason to suspect differences in the quality of school discipline data in EWIMS schools and control schools, school discipline records are generally

less valid and reliable than other student data because schools may underreport behavioral incidents and are inconsistent in reporting suspensions and identifying behaviors serious enough to warrant disciplinary action (Irvin, Tobin, Sprague, Sugai, & Vincent, 2004; Morrison, Peterson, O'Farrell, & Redding, 2004).

- Finally, some student outcomes could be affected by teacher awareness of or involvement in the EWIMS process. For example, a teacher in an EWIMS school could choose to give a student a passing, instead of a failing, grade to keep that student off the "flagged" list. In other words, it is possible some of the estimated impacts may reflect changes in how teachers react to student behaviors rather than to changes in those behaviors. However, this possibility is less plausible for attendance data, which more clearly reflect student, not teacher, behavior. Studying data on other outcomes (such as test scores) could further address this possible limitation.

Appendix A. Planned implementation of the Early Warning Intervention and Monitoring System

This appendix provides detail about school implementation of the Early Warning Intervention and Monitoring System (EWIMS).

Early Warning Intervention and Monitoring System training activities and timeline

Schools were randomly assigned in March 2014, and initial trainings occurred between April 2014 and June 2014. However, full implementation of EWIMS did not begin until the 2014/15 school year (table A1). During implementation, EWIMS schools were provided access to the EWIMS early warning data tool, print resources, and systematic support from a team of technical assistance liaisons. The liaisons were former educators and administrators, as well as researchers with expertise in dropout prevention strategies. The trainings that the technical assistance liaisons provided included:

- *Early warning data tool training.* On-site, in-person tool training was offered in spring 2014. These hands-on training sessions lasted approximately two hours and provided guided opportunities for participants to load data into the tool and run reports.
- *Regional trainings.* In-person regional training was offered in May and June 2014 to all members of each EWIMS school's team (approximately five to seven members). This training provided opportunities to learn about the seven-step EWIMS process through a variety of team-based and group activities. The six-hour training was hosted regionally in close proximity to two to five EWIMS schools at a time.
- *Early warning data tool refresher training.* The on-site, in-person tool training was followed by an online refresher training at the beginning of the 2014/15 school year (August–October 2014).
- *Site visits.* On-site support was offered three times to EWIMS schools during the 2014/15 school year—typically in the fall, winter, and spring. Site visits included brief presentations on EWIMS topics and full EWIMS team meetings guided by one of the EWIMS technical assistance liaisons. Additional activities were tailored to each school's individual needs. Each site visit lasted two to four hours.
- *WebShares.* The EWIMS technical assistance liaisons hosted five WebShares using a webinar platform during the 2014/15 school year to provide professional development to EWIMS schools. The WebShares also allowed EWIMS team members to share their successes and challenges and to establish communities of practice among EWIMS schools. Each of the five WebShares was offered on multiple days and times to allow for broad participation. At least one member of the EWIMS team at each school was expected to participate.
- *Responsive technical assistance.* The liaisons also provided responsive technical assistance to the schools throughout the implementation period. As schools encountered challenges, they were encouraged to reach out to their assigned liaison to request assistance. This support was provided on an as-needed basis.

Early Warning Intervention and Monitoring System team meetings

A broad, well-informed school-based EWIMS team was considered by the developers of the model to be important for implementation success. According to the model and associated guidance, the EWIMS team may be established as a new team or may build on or be integrated into an existing team (for example, a school improvement team, response to

Table A1. Timeline of technical training and implementation schedule for Early Warning Intervention and Monitoring System schools during the 2013/14 and 2014/15 school years

2014									2015					
Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Technical training schedule														
Early warning data tool training				Refresher early warning data tool training										
	Regional training on the seven steps													
				Site visit 1					Site visit 2			Site visit 3		
						Web-Share 1	Web-Share 2		Web-Share 3			Web-Share 4	Web-Share 5	
School implementation schedule														
	Initial import of student data into early warning data tool for first- and second-year students and flagging of at-risk students[a]													
				Import student background characteristics and attendance data after the first 20 or 30 days and flag at-risk students; and import all student data after the first grading period for first- and second-year students and flag at-risk students[b]				Import all student data after the second grading period for first- and second-year students and flag at-risk students			Import all student data after the third grading period for first- and second-year students and flag at-risk students		Import all student data after the fourth grading period for first- and second-year students and flag at-risk students	
				Assign students to interventions, monitor progress, and revise intervention assignments (ongoing throughout the school year)										
				Initial team meeting[c]		Team meeting	Team meeting	Team meeting[d]		Team meeting	Team meeting	Team meeting	Final team meeting	

EWIMS is the Early Warning Intervention and Monitoring System.

a. The initial data import included uploading student demographics, a course catalog, and a list of all interventions available to students. If available, schools imported incoming risk data, including data from grade 8 for first-year students and data from the previous school year for second-year students.

b. The grading periods in the timeline are 9-week quarter grading periods. Schools using a trimester grading period schedule imported data in the fall (around November), winter (around February), and spring (around May).

c. EWIMS teams were expected to meet monthly to review students' risk status, assign students to interventions, and monitor students' progress in interventions.

d. Many schools held only one EWIMS team meeting during December and January, but then met more frequently throughout the rest of the year.

Source: Authors' compilation.

intervention team, or student support team). An existing team that takes on the responsibility to use the EWIMS tool for dropout prevention efforts should include a broad representation of staff within the school and, ideally, the administration (for example, principals, teachers, district administrators, specialists). Ideally, EWIMS teams also will have district and feeder school representation.

In this study, the EWIMS technical assistance liaisons asked each treatment school to form an EWIMS school-based team in April 2014 that consisted of an EWIMS team chair, a primary user of the early warning data tool, and three to five other members who had knowledge of individual students at the school and of the interventions available to students. The chair was responsible for organizing the EWIMS team, handling communications with the project's implementation team, and ensuring team members followed through on tasks. The primary user of the early warning data was responsible for preparing and importing data into the early warning data tool, providing other team members access to the tool by managing user accounts, and ensuring the data and reports were available. Other team members were responsible for attending team meetings and following through on action items assigned by the team. The roles described could have been filled by one or more individuals at their discretion. Each team was responsible for fulfilling these roles in some way.

The EWIMS school-based team was expected to conduct the bulk of its work in the context of monthly meetings. It was expected that teams would meet at least once per month throughout the 2014/15 school year, with approximately 10 meetings per school. An agenda for each upcoming meeting was to be prepared at the end of the prior meeting, with standing agenda items including reviews of the data from the early warning data tool, actions taken for individual or groups of students, previous meetings' action items (ongoing or completed), new action items, and communication with staff and leadership. Notes were to be taken at each meeting and were to include action items assigned to specified individuals to accomplish. Agenda, meeting notes, and a faculty/staff sign-in sheet were be kept on file to provide a record of the team's work.

Importing data into the early warning data tool, and documenting students' assignment to interventions

A member of the EWIMS team was responsible for importing data into the tool to facilitate the EWIMS team's use of the early warning indicator data. Participating schools were expected to upload attendance data after the first 20 or 30 days of school and after every grading period. Course performance, grade point averages, and behavioral data were also expected to be uploaded after every grading period.

The EWIMS team member responsible for importing student data also was expected to import a list of interventions available in the school. EWIMS teams then were expected to use features within the tool to document their assignment of students to interventions, including dates. The EWIMS technical assistance liaisons encouraged EWIMS teams to match students with interventions and to monitor students' data and their at-risk status on the early warning indicators to inform ongoing decisions about the match between students and interventions.

Use of incoming risk flags during the 2014/15 school year

Use of the incoming risk flag in the EWIMS tool was not a major focus of implementation. The incoming risk flag was locally defined by schools using information from the prior year. The flag was not an automatic flag triggered by any particular data element in the tool (like those for chronic absence or course failure) but was imported by schools as part of the student demographic information. The EWIMS technical assistance liaisons advised schools to flag rising second-year students based on the off-track flag using data from their first year and to flag rising first-year students based on grade 8 data on attendance, course performance, behavior, or a list from middle school counselors. Data culled from the early warning data tool suggest that 23 of the EWIMS schools had at least some data in the incoming risk flag field. Among these 23 schools, first-year students more consistently had incoming risk flag data (45 percent) than did second-year students (38 percent). However, it is not clear what information each school used to determine incoming risk.

Appendix B. Recruitment, random assignment, and study sample

This appendix provides information about the study sample, including the recruitment and selection of participating schools, random assignment, school attrition, the analytic samples, and baseline equivalence.

Recruiting and selecting schools to participate in the study

The study aimed to recruit 72 high schools to provide sufficient statistical power to examine the impact of the Early Warning Intervention and Monitoring System (EWIMS) on student outcomes. Recruitment focused on three Midwest states that had an explicit focus on improving on-time graduation rates. None of the three states were implementing a statewide early warning system similar to EWIMS at the time of recruitment.

School eligibility criteria. Schools were eligible for the study if they had at least 130 grade 9 students, had an on-time graduation rate between 25 percent and 95 percent, were not using an early warning system, and were not using data in ways that closely mirrored the EWIMS seven-step process. Eligibility screening during recruitment focused on schools' existing practices related to the use of attendance and course performance data for identifying students who may be at risk of dropping out of high school, using these data to identify the root causes of chronic absences and course failure, and relying on these data to assign students to interventions to get students back on track. Attendance and course performance data were used in the eligibility screening because they were considered to be the most commonly available early warning indicators identified in prior related work. The screening did not focus on discipline or other types of data.

To operationalize schools' baseline data-driven dropout prevention efforts, each school was rated on a 6-point scale based on information gathered during a school screening interview and recruitment site visits. Definitions of schools' baseline data-driven dropout prevention efforts were as follows:

- 1 = very low data-driven dropout prevention efforts. Schools did not flag students as at risk of not graduating on time or assign students to interventions on the basis of course grades or attendance data in grades 9 and 10.
- 2 = low data-driven dropout prevention efforts. Schools flagged students as at risk of not graduating on time and assigned students to interventions on the basis of attendance but not course failure data in grades 9 and 10.
- 3 = moderate data-driven dropout prevention efforts. Schools flagged students as at risk of not graduating on time and assigned students to interventions on the basis of course failure but not attendance data in grades 9 and 10.
- 4 = high data-driven dropout prevention efforts. Schools flagged students as at risk of not graduating on time and assigned students to interventions on the basis of attendance and course failure data in grades 9 and 10, but were making little to no use of other data sources (for example, state test scores or formative assessments) to identify individual student learning needs and to understand root causes of risk indicators.
- 5 = very high data-driven dropout prevention efforts. Schools flagged students as at risk of not graduating on time and assigned students to interventions on the basis of attendance and course failure data and used other data sources (for example, state test scores and formative assessments) at the individual level to understand student-specific learning needs.

- 6 = using an early warning system. Schools were already using an early warning system to inform how they flagged students as at risk of not graduating on time and assigned students to interventions.

Schools with a score of 5 or 6 were deemed ineligible to participate; schools with a score of 4 or lower were considered eligible. Treatment and control schools were similarly distributed across the categories of baseline dropout prevention efforts; see the "Student and school baseline equivalence" section and table B5 later in this appendix for more detail.

Recruitment process. Recruitment took place during the 2013/14 school year. During recruitment, schools were first identified as potentially eligible based on size and on-time graduation rates using extant data. The study team contacted 688 potentially eligible schools (142 in State 1, 225 in State 2, and 321 in State 3) by email and follow-up phone call to provide an introduction to the project (table B1). Following this initial communication, 282 schools responded to emails and phone calls. Interested schools were invited to participate in a telephone screening interview. The purpose of the telephone screening interview was to learn more about the schools' use of data to identify at-risk students, their dropout prevention strategies, and any other initiatives that might interfere with their participation in EWIMS. During the telephone screening interview, the recruitment team also confirmed that the school's structure, size, and on-time graduation rate met the study's eligibility criteria. Of the 282 interested schools, 130 participated in a telephone screening interview. Of those 130 schools, 95 participated in site visits. The purpose of the site visit was to present the study and describe early warning systems generally and the EWIMS process, in particular, to school staff and to confirm that EWIMS would not duplicate school practices that existed at the time.

Table B1. Recruitment samples from the 2013/14 school year

Recruitment phase	Number of schools
Potentially eligible schools	688
School did not respond after first contact	406
Schools that responded after first contact (phone or email)	282
School did not respond after second contact	95
Recruitment team could not schedule screening interview	57
Schools that participated in the screening interview	130[a]
School declined to participate in the study	24
Entire school district declined to participate	2
Communication between recruitment team and school ceased	4
Recruitment team deemed the school ineligible for the study	27
School's on-time graduation rate exceeded eligibility criteria	4
School's processes too closely mirrored EWIMS (scored a 5 or 6 on the screening tool)	21
School structure (first- or second-year students housed on separate campuses)	1
School could not adhere to random assignment	1
Final recruited school sample	73

a. Of the 130 screened schools, 95 also received an in-person site visit. All 73 schools that participated in the study had a site visit.

Source: Authors' compilation.

Schools that remained interested and eligible. Seventy-three schools received and signed formal memoranda of understanding to participate in the project (see table B1). Although there was a target of 72 schools, 73 were included because the marginal cost of data collection for the last school was relatively low. This school was the third school in a district with three schools, and the associated data collection costs were low, given that data already was being collected from this district (table B2).

Description of the 73 recruited and participating schools. The 73 schools that signed formal memoranda of understanding to participate in the project varied in school size, on-time graduation rate, and baseline data-driven dropout prevention efforts. Schools were targeted for recruitment if they enrolled at least 130 grade 9 students. The majority of schools that joined the study had between 160 and 400 grade 9 students, and approximately a third of the schools enrolled more than 500 grade 9 students. Although schools with graduation rates between 25 percent and 95 percent were eligible to participate in the study, study schools typically had relatively higher graduation rates. In 2012/13, only 3 of the schools had graduation rates below 60 percent and only 6 had graduation rates below 75 percent; the majority of the schools had on-time graduation rates of 88 percent or higher.

Schools were eligible to participate in the study if they received a score below 5 on a 6-point scale in a screening protocol designed to capture data-driven dropout prevention efforts (the scores for this scale are described earlier in this appendix). The majority of participating schools had a score of 3 or lower on this 6-point scale.[12]

Random assignment

The 73 schools that signed a memorandum of understanding were randomly assigned to implement EWIMS (EWIMS schools) or continue their usual practices for identifying and supporting students at risk of not graduating on time (control schools). Random assignment was conducted using matched pairs and cluster randomization. Schools were matched using a Mahalanobis distance metric that describes how different any two schools are based on their graduation rates, school size, and baseline data-driven dropout prevention efforts (school eligibility score). The Mahalanobis metric is based on a measure of overall similarity ("Mahalanobis distance") between two units with respect to a pair of covariates. Mahalanobis distance is calculated on the basis of covariate differences between the units (for example, schools) and the sample variance–covariance matrix (Cochran & Rubin,

Table B2. Number of districts that had one or more eligible schools and the number of schools included in those districts

Number of study schools in the same district	Number of districts	Number of schools	Number of matched pairs for random assignment
1	58	58	29
2	4	8	4
3	1	3	1
4	1	4	2
Total	64	73	36

Source: Authors' compilation.

1973; Rosenbaum & Rubin, 1985; Rubin, 1980). Mahalanobis matching is appropriate in situations like this one, in which each school could potentially be matched with any other school in the pair.

Once all of the Mahalanobis distances had been calculated, the matched pairs were constructed using optimal matching, which minimized the total of the within-pair distances across all possible pairings. The optimal matching was conducted using a web application that implements the nbpMatching (Nonbipartite Matching) package in R written by Lu, Greevy, and Beck (2007). Because of the importance of the local context around dropout prevention (for example, state dropout prevention policies or district dropout prevention policies and practices), the matching procedure required an exact match on state (for example, a school in State 1 could be paired only with another school in State 1 and not with a school in State 2) and district in cases where more than one school in a district was recruited. The decision to force matches within district affected 7 of the 36 matched pairs (see table B2).

Next, one school within each matched pair was randomly assigned to the EWIMS group and the other to the control group. The only exception to this process was in one district with three recruited schools. In this district, the two schools that were most similar were matched with each other to create a pair and then each was randomly assigned to either the EWIMS group or the control group. The remaining school was then randomly assigned to either implement EWIMS or to the control group by a "coin flip." Thus, all schools in the study had a 50 percent chance of being assigned to EWIMS or the control group. Thirty seven schools were randomly assigned to implement EWIMS and 36 were randomly assigned to the control group.

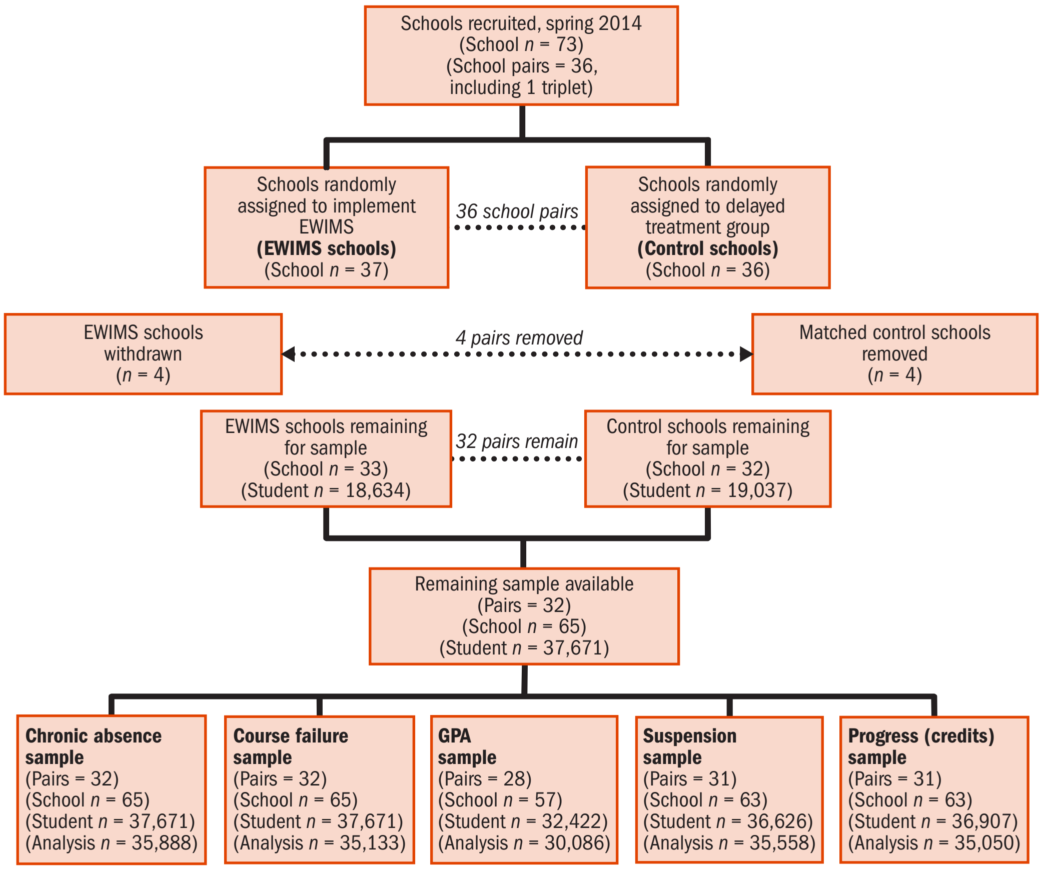
School attrition

Schools were considered to have attrited from the study only if they no longer participated in student-level data collection or if their matched pair counterpart did not participate in data collection.[13] In total, four EWIMS schools (and their matched pairs) formally withdrew from the study: these included two schools that had stopped implementing EWIMS and two EWIMS schools that implemented EWIMS but did not provide extant student data and were considered to have withdrawn. When a school officially withdrew from the study, the study team discontinued data collection for that school and its matched counterpart in the control group. Therefore, the four control schools that were matched to the four EWIMS schools that withdrew were also considered to have withdrawn, reducing the analytic sample from 73 schools to 65 schools (33 EWIMS schools, 32 control schools).

School and student analytic samples

School analytic sample. Because of attrition, the school analytic sample decreased from 73 to 65 schools (33 EWIMS and 32 control schools) for student-level analyses. The school analytic sample size also varied depending on levels of missing data for each outcome variable. For example, all 65 schools in the sample provided data on chronic absence and course failure, but only 63 schools provided data for suspensions and progress (credits earned) and only 57 schools provided grade point average (GPA) data. Thus, the school analytic samples differed by the outcome measure used in each model (figure B1).

Figure B1. School and student sample sizes from recruitment to analytic samples



EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: Four EWIMS schools could not be included in the sample because student outcome data were not provided. Of the four EWIMS schools, two stopped implementing EWIMS and withdrew from the study and two implemented EWIMS but did not provide student outcome data. The four control schools matched to these schools were also not included in the analytic sample. The student *n* represents the number of students present in the schools in the sample. The analysis *n* represents the number of students with nonmissing values on the outcome measure. Because students were missing values for each of the outcomes, the analysis *n* is smaller than the student *n* for each outcome.

Source: Authors' compilation.

For school-level analyses that relied on self-reported survey data (those that measured the treatment contrast or the impact of EWIMS on school data culture), schools were included in the sample if they responded to the survey. A total of 67 schools (33 EWIMS schools and 34 control schools) replied to at least one item on the school leader survey.

Student analytic sample. A total of 37,671 first- and second-year students in 65 schools provided at least one data element: 18,634 students in EWIMS schools and 19,037 students in control schools were included in the study (table B3).

The student analytic sample was reduced further due to missing student-level data. The student analytic samples ranged from 30,086 to 35,888 across outcomes (figure B1). The school and student sample sizes from recruitment and random assignment in March 2014 through data collection at the end of the 2014/15 school year are presented in figure B1. The samples for each analysis show the number of pairs, the number of schools, the

Table B3. Number of first- and second-year students and total sample size, by treatment group

Grade	Overall	EWIMS schools	Control schools
First-year students	18,748	9,217	9,531
Second-year students	18,923	9,417	9,506
Total	37,671	18,634	19,037

EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: This study followed two groups of students (first-year students and second-year students) in EWIMS schools and control schools. First-year students were enrolled in grade 9 in the 2014/15 school year; second-year students were enrolled in grade 9 in the previous (2013/14) school year and enrolled in either grade 9 or 10 in the 2014/15 school year.

Source: Authors' compilation.

number of students in each sample, and the number of students included in each analysis who were not missing outcome data.

Rates of missing data at the school and student levels

The extent of missing data at the school level varied across the different outcomes used in the primary impact models. Also, if a school failed to provide student-level data for an outcome measure, both it and its matched counterpart were dropped from the student-level analyses. As a result, there was no differential attrition between EWIMS and control schools at the school level due to missing data on outcome measures in the analytic samples. As a test of the robustness of the results, a sensitivity analysis was run that used a common analytic sample for all outcomes (see tables D1 and D2 in appendix D).

Within these analytic samples for each outcome, the percentage missing was calculated using a denominator equal to the number of students in the matched pairs of schools that provided data for each outcome. Data were missing for between 3 percent and 8 percent of students in the analytic samples, and there were no statistically significant differences in the level of missingness by condition (table B4).

Because the rates of missing data at the student level were low, the primary impact models did not use any missing data strategy to correct for missingness on the outcomes. As a sensitivity analysis, results were also estimated for models that adjusted for missingness on outcomes using inverse probability weighting. With this approach, students who were not missing the outcome measure were weighted to represent students who were (Puma, Olsen, Bell, & Price, 2009). These inverse probability weights were estimated using a model that contained the following covariates: state of residence, grade, whether the student was in an EWIMS school, all demographic variables, grade 8 test scores, and dummy variables representing each matched pair. The results are similar to those produced with the primary impact model specifications (see table D1 in appendix D).

Across the analytic samples, the percentage of students missing demographic covariates or the grade 8 state standardized test scores ranged from less than 1 percent to 21 percent for EWIMS schools and less than 1 percent to 18 percent for control schools. Age, gender, and race/ethnicity data were missing for less than 1 percent of students in EWIMS schools and control schools across each analytic sample. Data on English learner status and special education status (as indicated by having an Individualized Education Program) at baseline

Table B4. Number and percentage of students missing data for each outcome, by treatment group

Outcome	Overall			EWIMS schools			Control schools			Standardized difference (Hedges *g*)	*p*-value
	Analysis (number of students)	Missing (number of students)	Percent missing	Analysis (number of students)	Missing (number of students)	Percent missing	Analysis (number of students)	Missing (number of students)	Percent missing		
Chronic absence	35,888	1,783	5	17,411	1,223	7	18,477	560	3	0.17	0.144
Course failure	35,133	2,538	7	17,410	1,224	7	17,723	1,314	7	–0.01	0.934
Low GPA	30,086	2,336	7	15,253	1,005	6	14,833	1,331	8	–0.08	0.700
Suspended	35,558	1,068	3	17,557	541	3	18,001	527	3	0.01	0.285
Progress in school	35,050	1,857	5	17,499	743	4	17,551	1,114	6	–0.09	0.855

EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: Using a multilevel logistic regression model, the binary indicator of whether the outcome was missing was regressed on the treatment indicator that identified schools as EWIMS or control schools and a set of dummy variables that captured school matched pairs. The p-value was associated with the test of whether there was a statically significant difference in missing data by condition for each outcome.

Source: Authors' analysis based on extant student records from schools, school districts, and state education agencies described in appendix C.

were missing for 18 percent to 21 percent of students in EWIMS schools and for 15 percent to 18 percent of students in control schools. Data on eligibility for the federal school lunch program at baseline were missing for 22 percent to 26 percent of students in EWIMS schools and for 17 percent to 20 percent of students in control schools. Schools had a difficult time providing these data for the prior school year or before random assignment, especially for students who were in grade 9 in 2014/15. Across the analytic samples, grade 8 test scores in reading and math were missing for 18 percent to 21 percent of students in EWIMS schools and for 12 percent to 15 percent of students in control schools.

There was no differential missingness by condition for gender, racial/ethnic minority, and age data. However, there were statistically significant differences in the proportion of students with missing covariate data in EWIMS and control schools on state math and reading test scores and on baseline English learner status and special education status in certain analytic samples.

- Rates of missing data on grade 8 state math and reading test scores were higher in EWIMS schools than in control schools for some analytic samples, including the samples used to evaluate the impact of EWIMS on chronic absence, course failure, and grade point average.
- Rates of missing data on baseline English learner status and special education status were higher in EWIMS schools than in control schools for some analytic samples, including the samples used to evaluate the impact of EWIMS on all student-level outcomes except progress in school.

The differential missingness was addressed with the use of missing data flags and mean imputation for missing covariates in the analyses. Specifically, a dummy variable adjustment was used to retain in the primary impact models students who were missing data on one of the baseline covariates. Missing cases were set to a constant (the mean), and dummy indicators for missing data were included in the model. This strategy for handling missing covariate data has been shown to produce impact estimates and standard errors with low bias (Puma et al., 2009). As an additional check of the robustness of the results, models were also estimated without covariates (see table D1 in appendix D).

Student and school baseline equivalence

To determine if random assignment produced two groups of similar schools, baseline characteristics were analyzed for all schools and students in the intent-to-treat study sample and analytic samples. Baseline school characteristics included grade 9 enrollment and total school enrollment, on-time graduation rates, whether the school was categorized as moderate or high on baseline data-driven dropout prevention efforts as assessed during recruitment, the percentage of students eligible for the federal school lunch program, and the percentage of racial/ethnic minority students.

Baseline student characteristics included grade 8 standardized state test scores in reading and math, gender, racial/ethnic minority status, English learner status, special education status, and eligibility for the federal school lunch program.

In the intent-to-treat sample of all 73 schools, baseline equivalence was achieved across all school-level baseline measures (table B5). EWIMS and control schools had similar baseline school size (both grade 9 and total enrollment), on-time graduation rates, data-driven dropout prevention efforts, and student characteristics. EWIMS and control schools also served student populations with similar demographic characteristics and prior achievement on state assessments in reading and math (see table B5).

Baseline equivalence within each analytic sample was also examined. Baseline characteristics by condition were not significantly different for any of the analytic samples, and all standardized differences were 0.20 or less, with one exception. In the analytic sample for GPA, EWIMS schools had an average of 41 percent of students eligible for the federal school lunch program, control schools had an average of 45 percent, a standardized difference of –0.22 that was not statistically significant at the $p < 0.05$ level.

The study team examined the baseline equivalence by grade. Contrasts of the 13 baseline characteristics by condition yielded no statistically significant differences at the $p < 0.05$ level for the first-year student or second-year student samples. All standardized differences of the baseline characteristics within grade were less than 0.20.

Table B5. Baseline characteristics of schools and students in the randomly assigned sample, overall and by condition prior to random assignment in March 2014

	Overall				EWIMS schools				Control schools					
Characteristic	School *n*	Student *n*	Mean	Standard deviation	School *n*	Student *n*	Mean	Standard deviation	School *n*	Student *n*	Mean	Standard deviation	Standardized difference	*p*-value
School characteristics														
Grade 9 school enrollment	73	na	321.34	142.84	37	na	318.97	137.54	36	na	323.78	150.01	–0.03	0.687
Total school enrollment	73	na	1,213.52	546.22	37	na	1,165.03	523.96	36	na	1,263.36	571.25	–0.18	0.156
On-time graduation rate (%)	73	na	86.92	7.93	37	na	86.72	9.03	36	na	87.13	6.74	–0.05	0.839
High baseline data-driven dropout prevention efforts (%)[a]	73	na	61.64	48.96	37	na	59.46	49.77	36	na	63.89	48.71	–0.09	0.567
Eligible for the federal school lunch program (%)	73	na	42.79	18.63	37	na	41.18	18.53	36	na	44.45	18.84	–0.17	0.239
Racial/ethnic minority enrollment (%)	73	na	24.03	26.24	37	na	23.80	26.88	36	na	24.26	25.94	–0.02	0.689
Student demographic characteristics														
Female (%)	65	37,541	48.85	49.99	33	18,568	49.13	49.99	32	18,973	48.57	49.98	0.01	0.284
Racial/ethnic minority status (%)	65	37,545	24.67	43.11	33	18,564	26.20	43.97	32	18,981	23.18	42.20	0.07	0.906
Students in special education (%)	65	30,482	13.29	33.94	33	14,760	13.30	33.96	32	15,722	13.27	33.93	0.00	0.932
English learner students (%)	65	30,481	2.99	17.04	33	14,760	3.16	17.49	32	15,721	2.84	16.60	0.02	0.288
Eligible for the federal school lunch program (%)	62	29,711	43.77	49.61	31	14,213	45.59	49.81	31	15,498	42.11	49.37	0.07	0.921
Student prior achievement														
Grade 8 state standardized test scores in reading	62	31,165	612.01	161.80	30	14,903	615.43	161.21	32	16,262	608.87	162.27	–0.05	0.871
Grade 8 state standardized test scores in math	62	31,196	628.34	152.59	30	14,903	632.52	151.13	32	16,293	624.52	153.81	–0.04	0.488

EWIMS is the Early Warning Intervention and Monitoring System. *n* is the number of schools or students. na is not applicable because these are characteristics at the school level.

Note: None of the differences between groups of schools or groups of students were statistically significant at the $p < .05$ level. Hedges' g was used to compute the standardized difference. A linear regression model with a treatment indicator that identifies schools as EWIMS schools or control schools and a set of dummy variables that captures school matched pairs was used to test the school characteristic differences. A multilevel linear regression model with students at level 1 and schools at level 2, a treatment indicator, and a set of dummy variables that captures school matched pairs was used to test the student characteristic differences.

a. This measure is the percentage of schools scoring 3 or 4 (moderate or high) on the scale, while omitting those schools scoring 5 or 6 (very high), since they were not included in the study.

Source: Authors' analysis based on school characteristics from 2012/13 and extant student records from schools, school districts, and state education agencies described in appendix C. Extant student records from the 2012/13 school year are used for the second-year students, and data from the 2013/14 school year are used for the first-year students.

Appendix C. Data collection and analytic methods

This appendix provides detail about the methods used in the study, including the data sources, data collection, and analytic methods for each research question.

Description of data

The following types of data were collected:

- Extant student records from schools, school districts, and state education agencies for students in schools implementing the Early Warning Intervention and Monitoring System (EWIMS) and control schools between the 2012/13 school year and the end of the 2014/15 school year. These data were used for student background characteristics and to operationalize student outcomes.
- School characteristics of participating schools that are publicly available from the Common Core of Data (CCD) and state education agencies (U.S. Department of Education, 2015). These data were used for random assignment and baseline equivalence.
- School leader responses on a web-based survey, administered in spring 2015, to measure school data culture, collect information about the number and type of interventions used to support at-risk students in EWIMS and control schools, and operationalize the treatment contrast. The survey was also administered in spring 2014, and data from this administration were used only as an additional data source for identifying interventions offered in EWIMS schools.
- Extant documents on EWIMS implementation collected between spring 2014 and spring 2015 by the EWIMS technical assistance liaisons for EWIMS schools only (for example, attendance sheets and school implementation summaries).
- Monthly logs recording the content and frequency of EWIMS team meetings during the 2014/15 school year in EWIMS schools only.
- Reports from early warning data tools that captured tool use through spring 2015 in EWIMS schools only.
- Interviews with EWIMS team members administered in spring 2015 in EWIMS schools only.

Data are displayed by research question in table C1.

Table C1. Data from the 2012/13, 2013/14, and 2014/15 school year used to address each research question

Research questions	Data elements	Data sources	Data time frame
Impact 1: What is the impact of EWIMS on indicators of student risk?	• Student demographic characteristics • Grade 8 test scores (prior achievement) • Chronic absence (total number of absences for the school year) • Course failure (course titles and course grades) • Grade point average • Suspension (suspensions and expulsions)	State education agencies, school districts, schools	2012/13 and 2013/14 for prior achievement; 2014/15
Impact 2: What is the impact of EWIMS on student progress in school?	• Student demographic characteristics • Grade 8 test scores (prior achievement) • Credits earned	State education agencies, school districts, schools	2012/13 and 2013/14 for prior achievement; 2014/15
Exploratory 1: What is the impact of EWIMS on school data culture?	• School data culture (context for data use, concrete supports for data use, data-driven student support, and barriers to data use)	School leader survey	Spring 2014/15
Implementation 1: To what extent did EWIMS schools participate in the professional development provided and implement the EWIMS seven-step process?	• Participation in EWIMS training • EWIMS training satisfaction surveys • Level of implementation of the seven-step EWIMS process	School leader survey, EWIMS monthly logs, early warning data tool reports, EWIMS team interview, extant documents on EWIMS implementation	April 2014–June 2015
Implementation 2: What barriers to implementation did EWIMS schools experience?	Barriers	School leader survey, EWIMS monthly logs, early warning data tool reports, EWIMS team interview (and exit interviews), extant documents on EWIMS implementation	April 2014–June 2015
Implementation 3: What types of interventions did EWIMS schools provide to students identified as at risk, and what percentage of students received those services?	Student assignment to interventions	School leader survey, early warning data tool reports, EWIMS team interview	April 2014–June 2015
Implementation 4: To what extent did EWIMS and control schools differ in their practices for identifying and supporting students at risk of not graduating on time?	Frequency of data review on attendance and course performance, interventions available to support students, the presence of an early warning system and dedicated team to identify and support at-risk students	School leader survey	June 2015

EWIMS is the Early Warning Intervention and Monitoring System.

Source: Authors' compilation.

Data were requested for all participating schools. Of the 73 schools that were randomly assigned to the EWIMS and control group samples, the school-level data collection rates of the individual data elements ranged from 78 percent to 95 percent: 78 percent to 95 percent for EWIMS schools and 86 percent to 94 percent for control schools (table C2). School-level data sources with student-level data could have missing student data. Student-level missing data are detailed earlier as part of the description of samples and attrition (see appendix B).

Extant student records. All student-level data were collected from extant records from state education agencies, districts, and the schools themselves, depending on the data element; there was no student-level primary data collection burden on schools. For the second-year students (students in grade 9 in 2013/14), baseline data were collected from the 2012/13 school year and for the first-year students (students in grade 9 in 2014/15), baseline data were collected from the 2013/14 school year. Student outcome data were collected for the 2014/15 school year for first- and second-year students. The data collection rates for the individual data elements ranged from 78 percent to 89 percent for EWIMS schools and 86 percent to 89 percent for control schools (see table C2). Of the 73 schools randomly assigned to the EWIMS and control group samples, 75 percent provided all of the extant

Table C2. School-level data collection rates, by condition and overall, during the 2014/15 school year

Data collected	EWIMS schools (*n* = 37) Percent	Control schools (*n* = 36) Percent	All schools (*n* = 73) Percent
School characteristics			
School leader survey (spring 2015)	89	94	92
Implementation summaries from EWIMS school liaisons	78	na	na
EWIMS training satisfaction surveys[a]	95	na	na
EWIMS monthly logs	89	na	na
Early warning data tool reports	84	na	na
EWIMS team interviews (and exit interviews)	95	na	na
Extant student records			
Grade level	89	89	89
Demographic characteristics	84	89	86
Grade 8 test scores	81	89	85
Attendance	89	89	89
Course failure	89	89	89
Grade point average	78	86	82
Suspension	86	89	88
Credits earned	86	89	88
Enrollment and exit codes	84	89	86

na is not applicable because these data were not collected from control schools. EWIMS is the Early Warning Intervention and Monitoring System. *n* is the number of schools or students.

Note: Only two schools are missing demographic records, and records are missing only eligibility for the federal school lunch program.

a. Satisfaction surveys were collected after each of the 11 EWIMS trainings, and response rates ranged from 60 percent to 95 percent. Most satisfaction survey response rates were above 80 percent (for 9 of the 11 trainings); the two exceptions were site visit 1 (78 percent) and site visit 2 (60 percent).

Source: Authors' compilation.

student records, including grade level, demographic characteristics, grade 8 test scores, attendance, course failure, grade point averages (GPA), number of suspensions, credits earned, and enrollment and exit codes. Seventy-seven percent of the 73 schools provided all of the extant student records to operationalize the outcome measures (that is, chronic absence, course failure, low GPA, number of suspensions, and progress in school).

The data elements collected included the following:

- *Demographic characteristics.* Measures included date of birth, gender, race/ethnicity, special education status (as indicated by having an Individualized Education Program), English learner status, eligibility for the federal school lunch program, and grade level. Age was calculated as of September 1, 2013, using the date of birth variable. Race/ethnicity was coded into binary indicators denoting whether students represented racial/ethnic minority groups. Gender, special education status, English learner status, and eligibility for the federal school lunch program were coded as binary indicators. Grade level in the 2013/14 and 2014/15 school years was used as an indicator of the grade level for each student.
- *Grade 8 state standardized tests.* Grade 8 reading and math scores from the 2012/13 and 2013/14 school years served as measures of prior achievement for the second-year students and first-year students, respectively, in the primary impact models. Grade 8 test scores in reading and math were standardized using the mean and standard deviation for the sample within each state and grade (z-scores).
- *Attendance.* Attendance data included the total number of absences and total days enrolled in the 2014/15 school year. Total number of absences included excused and unexcused absences. Absences and enrollment counts were provided by days, hours, or class periods, depending on how attendance was reported for the school year by the school, district, or state education agency.
- *Course failure.* Course data included course name and course grade for all courses attempted for the first- and second-year students in the study schools during the 2014/15 school year.
- *Grade point averages.* GPA data included cumulative high school GPA through the 2014/15 school year for the first- and second-year students in study schools.
- *Suspensions.* Suspension data included total number of suspensions or total days suspended in the 2014/15 school year. For some schools, 22 in total, it was not clear which was provided. "Total suspensions" combines in-school and out-of-school suspensions.
- *Credits earned.* Credits data included the cumulative number of high school credits earned through the 2014/15 school year for the first- and second-year students in study schools.

School characteristics. The following school-level extant data were collected for the 73 study schools to inform random assignment and to assess baseline equivalence. Grade 9 enrollment records and on-time graduation rates were used to create the matched pairs for random assignment. These data were publicly available from the CCD and state education agencies for 100 percent of the study schools (U.S. Department of Education, 2015). The data collected include the following:

- *School size.* School size data included the total number of grade 9 students and the total student enrollment for each school from the CCD for the 2012/13 school year (U.S. Department of Education, 2015). These 2012/13 data were used in the assessment of baseline equivalence and as covariates in the regression analyses for treatment contrast and school data culture. The study team also used publicly available grade 9 enrollment records retrieved from the three state education agency websites for the 2011/12 school year for random assignment because these were the most recent data on school size available.

- *On-time graduation rates.* On-time graduation rate data included four-year high school graduation rates from 2011/12 and 2012/13 for each study school from the websites of the three state education agencies. The study team used on-time graduation rates from 2011/12 for random assignment because they were the most recent data available. The on-time graduation rates from 2012/13 were used to examine the equivalence of EWIMS and control schools at baseline, before training began for the EWIMS schools in April 2014.
- *Percentage of students who were eligible for the federal school lunch program.* The total number of students eligible to participate in the federal school lunch program was collected for the 2012/13 school year from the CCD (U.S. Department of Education, 2015). The percentage for each school was calculated by dividing the number of eligible students by the school's total student enrollment.
- *Percentage of students who identified as a member of a racial/ethnic minority.* Data on race/ethnicity for the 2012/13 school year were collected from the CCD (U.S. Department of Education, 2015). The percentage of racial/ethnic minorities for each school was calculated by summing the total number of students who identified as American Indian/Alaska Native, Asian, Black, Hawaiian Native/Pacific Islander, Hispanic, or two or more races and dividing by the school's total student enrollment.

School leader survey. A web-based survey was administered to one school administrator at each EWIMS school and control school at the end of the 2014/15 school year. Surveys were also administered in spring 2014, but these data were used only to gather information on EWIMS schools' interventions. The 2015 surveys were used to do the following:

- Measure school data culture.
- Collect information about the interventions used to support at-risk students.[14]
- Document the treatment contrast between EWIMS and control schools.

School leaders who were the designated contacts for the study or who were knowledgeable about the interventions available for at-risk students at their school were asked to participate in the survey. Respondents included principals, assistant principals, guidance counselors, and school coordinators. The school leader survey response rate in spring 2015 was 90 percent (66 schools).[15]

School data culture measures. School data culture refers to the ways schools use data to inform decisions about supports for students. Items from an earlier study about the use of benchmark assessment data to inform instructional decisions (Faria et al., 2012) were adapted for use in the current study. The school leader survey included 53 items, most with 4-point response scales, as well as some frequency count questions to measure the frequency of data use practices. The survey included four subscales: context for data use, concrete supports for data use, data-driven student support, and barriers to data use.

- *Context for data use.* School goals for data use and the professional climate around data use.
- *Concrete supports for data use.* The presence or absence of structured time to review data, training and professional development about data use, the availability of data coaching, and principal leadership.

- *Data-driven student support.* The frequency, duration, mode, and type of data review, as well as the ways teachers and schools respond to student data, including assigning general and targeted interventions, determining teacher professional development needs, and informing school improvement plans.
- *Barriers to data use.* Staff and logistical barriers to data use, such as lacking time to review data or not having access to data that are timely and actionable.

Rasch analyses for ordered response categories (Rasch, 1960 [1980]) were used to determine whether the survey items, as well as each subscale, reliably measured the latent constructs of overall school data culture. The Rasch approach differs from classical test theory (averaging the percentage of respondents endorsing each response option) because the Rasch model considers the relative frequency with which each item and response option is used (that is, item difficulty).[16] The resulting scale scores provided a quantitative view of the frequency and intensity of respondents' answers across a set of items representing school data culture. The subscales and overall measure of school data culture had high internal consistency, with Cronbach's alpha reliability coefficients for the scales ranging from 0.80 to 0.97 (table C3).

Table C3. School data culture scale and subscales during the 2014/15 school year

Scale and subscales	Number of items	Example items	Example response options	Cronbach s alpha
School data culture	53			0.97
Context for data use	9	How much do you agree or disagree with the following statements about how your school uses data? This school has clear goals for using data to improve student outcomes.	• Strongly agree • Agree • Disagree • Strongly disagree	0.81
Concrete supports for data use	12	In the last 12 months, how much did the professional development at your school emphasize the following? Using data to target interventions for low-performing students.	• Major emphasis • Moderate emphasis • Minor emphasis • No professional development provided on this topic	0.92
Data-driven student support	23	Please indicate the extent to which your teachers do each of the following: meet together to look at trends in the data (or analyze data).	• To a great extent • To a moderate extent • To a slight extent • Not at all	0.92
Barriers to data use	9	To what extent do the following factors hinder your ability to use student data to inform instruction and interventions? Lack of time to study and think about available data.	• To a great extent • To a moderate extent • To a minor extent • Not at all	0.80

Note: The school data culture instrument can be obtained by contacting the first author of this report.

Source: Authors' analysis based on school leader survey.

Extant documents on EWIMS implementation from the technical assistance liaisons. Extant data from the EWIMS technical assistance liaisons included attendance sheets from all trainings, completed school implementation summaries, and customized support plans. Attendance sheets were used to examine EWIMS schools' participation at each professional development session. Each EWIMS school's technical assistance liaison completed an implementation summary at the end of the 2014/15 school year for each school that did not cease implementation. The school summaries and customized technical assistance plans provided information on the successes and challenges schools experienced with each step of the EWIMS seven-step process and a summary of the technical assistance provided for each school. Extant documents from implementation were used to examine the level of implementation at each participating EWIMS school (using a rubric described in the "Implementation analyses" section later in this appendix).

EWIMS training satisfaction surveys. Satisfaction surveys were collected after each training to document satisfaction with EWIMS implementation. The satisfaction surveys gauge participants' satisfaction with the quality, relevance, and usefulness of the service provided. Satisfaction surveys for the in-person trainings (regional, early warning data tool training, and site visits one through three) were paper based and administered in person. Satisfaction surveys for the online trainings (early warning data tool refresher and WebShares one through five) were web based and administered electronically.

The number of participants expected at each type of training varied. The expectation for on-site, in-person trainings (regional trainings and site visits) was that the full EWIMS team would participate. Satisfaction survey response rates for training activities with EWIMS teams are presented at the individual participant level (table C4).

Response rates for satisfaction surveys from the in-person trainings ranged from 60 percent to 88 percent across all schools, with the regional training having the highest response rate (see table C4). The response rates were calculated from the number of schools where at least one participant responded to the survey. The expectation for tool trainings and WebShares was that at least one representative from each school would participate. Response rates for the training activities for which only one school representative was expected to participate ranged from 86 percent (WebShare 1) to 97 percent (early warning data tool training; table C5).

EWIMS monthly log data. EWIMS teams at each school were asked to keep logs of the team meetings as part of typical implementation, and the expectation was that teams were meeting monthly. Meeting logs were collected from the EWIMS schools at the end of each month to document the frequency and content of meetings. EWIMS schools were

Table C4. Participant-level satisfaction survey response rates for on-site visits with Early Warning Intervention and Monitoring System teams in the 2014/15 school year

Training	Timing	Number of completed satisfaction surveys	Total number of participants	Response rate (percent)
Regional training	Spring 2014	173	196	88.3
Site Visit 1	Summer 2014	174	224	77.7
Site Visit 2	Winter 2014–15	84	139	60.4
Site Visit 3	Spring 2015	108	163	66.3

Source: Study records.

Table C5. School-level satisfaction survey response rates in the 2014/15 school year

Training	Timing	Number of completed satisfaction surveys	Total number of participants	Response rate (percent)
Early warning data tool training	Spring 2014	35	36	97.2
Early warning data tool refresher training	Fall 2014	32	35	91.4
WebShare 1	Fall 2014	24	28	85.7
WebShare 2	Winter 2014–15	20	23	87.0
WebShare 3	Winter 2015	20	22	90.9
WebShare 4	Spring 2015	19	22	86.4
WebShare 5	Spring 2015	18	19	94.7

Source: Study records.

provided a log template they could use for their EWIMS team meetings, and the meeting logs recorded the meeting participants, agenda, meeting activities, and action items. Most schools opted to use the meeting log template, but some schools provided notes from the meeting instead of or in addition to the meeting log.

Between June 2014 and June 2015, 35 EWIMS schools (95 percent) held at least one EWIMS team meeting, and 33 schools (89 percent) submitted at least one meeting log. In total, 217 EWIMS team meetings were held throughout the implementation period, and monthly logs were collected from 207 team meetings (95 percent).

Early warning data tool reports. Reports generated from the early warning data tools captured tool use and were requested from EWIMS schools during the 2014/15 school year after each quarter, trimester, or semester, depending on each school's grading period. The tool produced four summary reports that were exported as xml files:

- *Student Flag Report.* This report displayed a list of all students identified for different indicators of risk: chronic absence, course failure, low GPA, or behavior (e.g., suspensions). For each indicator, a student was flagged by the tool if the student had data imported into the tool and met the research-based indicators of risk programmed into the tool.
- *Data Import Report.* This report recorded the date and time when files were imported by a school into the early warning data tool. Importing student demographic data and initial data on output indicators is a required step prior to using the tool.
- *Student Intervention Report.* This report contained each student-specific intervention assigned to a student in the early warning data tool. The report included the intervention name, type (for example, academic, behavioral, chronic absence), and the start and end dates for each student assigned to the intervention.
- *Student Data Report.* This report consisted of the actual student data uploaded into the tool, including student demographics (gender, race/ethnicity, identified disability, and English learner and economic status), incoming risk flag, attendance, course failure, GPA, behavioral, and cumulative credits data. This report documented the completeness of the data that schools uploaded into the tool (that is, the percentage of students for whom demographic and administrative data records were uploaded).

The most recent early warning data tool reports for the 2014/15 school year were used for the implementation analyses. Thirty-one EWIMS schools (84 percent) shared all four tool reports at least once. Data from the early warning data tool were coded according to the implementation rubric, detailed in the "Implementation analyses" section later in this appendix.

EWIMS team interview. In spring 2015, EWIMS team members were interviewed to collect qualitative information about how each school implemented the EWIMS model. The interview protocol covered each step of the seven-step implementation process and asked questions about the progress, successes, and challenges encountered at each step. The EWIMS team chairperson, the data designee, and up to one other team member were invited to participate in the interview. Twenty-eight of the EWIMS teams participated in the interview (76 percent).

Exit interviews were conducted with seven of the eight schools that stopped, or never began, implementing EWIMS during the 2014/15 school year; the one school that dropped out of the study after random assignment but before implementation was not interviewed. These schools received a modified version of the team interview that focused on the reasons why they chose not to implement EWIMS. Each interview was transcribed and coded according to the implementation rubric, described in the "Implementation analyses" section later in this appendix.

Treatment contrast. The study was designed to minimize the use of an early warning system similar to EWIMS in control schools in multiple ways. These included screening out schools from the study sample that used an early warning system or used data in ways that mirrored the EWIMS seven-step process, as well as giving all control schools access to all features of EWIMS the following school year at no cost (a delayed treatment design). Also, attendance records from EWIMS trainings demonstrate that no control schools accessed the professional development offered in the study. Nevertheless, it is still important to describe whether and how EWIMS and control schools differed in their practices related to identifying and supporting at-risk students during the year of the evaluation.

This study did not collect student-level information about the treatment contrast (for example, detailed data in control schools about practices related to reviewing student data, assigning interventions, and monitoring student progress). The process of tracking this information would resemble the implementation of EWIMS, so that collecting these data might have diminished the contrast between EWIMS and control schools.

Instead, the treatment contrast was measured with the 2015 school leader survey using items that captured the extent to which schools adhered to the practices of their randomly assigned groups by using or not using an early warning system. Beyond self-reported use of an early warning system, the study also examined contrasts between EWIMS and control schools in some early warning system–related practices, including whether schools reported having a dedicated team to identify and support at-risk students, school self-reported frequency of attendance and course failure data review, and the number and type of interventions offered to students. Leaders from 67 of the 73 schools (90 percent) responded to these items.

To measure the extent to which schools adhered to their randomly assigned groups, the survey asked school leaders to indicate whether they used an early warning system. The survey wording was as follows:

Is your high school using an early warning system to identify students who may be at risk of not graduating from high school on time? Response options were as follows:

- *Yes, we are using an early warning system at my high school.*
- *No, my high school is not currently using an early warning system.*

All school leaders participated in presentations during the recruitment process that provided an overview of early warning systems and EWIMS before signing memoranda of understanding to adopt EWIMS in either the treatment or delayed-treatment condition. Specifically, school leaders received materials indicating that early warning systems rely on readily available data housed at the school to help predict which students are at risk of not graduating on time; target resources to support off-track students while they are still in school, before they drop out; and examine patterns to identify potential school climate issues. The materials further indicated that early warning systems use key indicators of engagement (attendance), course performance (course grades, credits earned, GPA), and behavior (suspensions) to flag at-risk students.

The survey also asked school leaders to report whether or not they had a dedicated team to identify and support at-risk student. The survey wording was as follows:

Does your school have a team or group of individuals that reviews student data to support students who are identified as at risk of not graduating from high school (for example building- or teacher-level teams, student success teams, data review teams)? The response options were as follows:

- *Yes, we have a dedicated school-based team.*
- *No, we do not have a dedicated school-based team.*
- *Other.*

In the memoranda of understanding, under roles and responsibilities, all schools participating in the study agreed as part of the EWIMS implementation "to develop an EWIMS team within their school" that would be responsible for "identifying students who are at risk and ensuring that their individual needs are met through school-based interventions." Therefore school leaders who responded to the survey, unless these were new due to staff turnover, had shared definitions of an early warning system and the school-based team to identify and support at-risk students as conceptualized for this study. However, one limitation of the survey item assessing whether schools had a school-based team was that the item did not provide a response option for a nondedicated school-based team.

Items used to measure frequency of review of attendance and course performance data for treatment contrast analyses are shown in table C6. While both items were measured on ordinal response scales, they were operationalized into a binary indicator of whether or not schools reviewed these data at least monthly. The monthly cut-off was most appropriate given the frequency with which data are made available and the expected frequency of EWIMS team meetings (monthly).

Table C6. Survey items regarding frequency of data review used in the 2014/15 school leader survey

Survey item	Response options
Does your school review student attendance data to determine which students may be at risk (that is, missing more than a certain number of days per year)?	• Yes • No
Does your school review student course failure data (including course failures, credit deficiencies) to determine which students may be at risk?	• Yes • No
How often do you review these [attendance] data?	• Daily • Weekly • Monthly • Four times per year (once per quarter) • Three times per year • Two times per year • One time per year
How often do you review these [course failure] data?	• Daily • Weekly • Monthly • Four times per year (once per quarter) • Three times per year • Two times per year • One time per year

Source: Authors' compilation.

The school leader survey also asked about the types of dropout prevention interventions and strategies that were available for students in EWIMS and control schools. These items were based on the constructs presented in *Dropout Prevention: IES Practice Guide* (Dynarski et al., 2008) and *Approaches to Dropout Prevention: Heeding Early Warning Signs with Appropriate Interventions* (Kennelly & Monrad, 2007). They survey items asked respondents to provide the name and focus (chronic absence, course failure, behavioral, or a combination) of each intervention (table C7).

The number of interventions offered in EWIMS and control schools was tallied using the data collected in the school leader survey and summarized in two ways. First, to generate a count of the number of interventions offered, the number of interventions used to address

Table C7. Survey items used to document number and type of interventions used in the 2014/15 school leader survey

Survey item	Response options	
Program name	Fill in the blank	
Specific focus of the intervention (for example, math, Algebra I remediation, reading, study skills, social emotional, peer mentoring, attendance, mental health)	Fill in the blank	
Type of intervention	• Targeted academic interventions • Targeted behavior interventions • Attendance or truancy interventions • Online content recovery programs	• Mentoring programs • Internship or school-related work-preparation programs • College preparation

Source: Authors' compilation.

chronic absence, academic performance, and behavioral issues was summed. Each EWIMS and control school was also coded as either offering interventions supporting all three categories of risk or as not offering them.

Operationalizing student outcome data

Main student outcomes. To create the main student-level outcome measures, the extant student data were coded as 1 or 0, reflecting the presence or absence of an indicator of risk of a student's not graduating on time or not progressing in school. The thresholds used to create the binary indicators for chronic absence, course failure, low GPA, and suspensions were based on the thresholds that are used in the early warning data tool to identify students as at risk of not graduating on time (Heppen & Therriault, 2008; Therriault et al., 2010). The thresholds for progress were established for the study. Each outcome variable was coded into the binary indicator used in the analyses testing the primary impact questions (table C8).

Outcomes not measured or measured with limitations. States, districts, or schools considering investing in an early warning system such as EWIMS may be interested in knowing the impact of the model on a number of additional outcomes that were beyond the scope of this study or were available on only a limited basis. These outcomes include persistence in school, dropout rates, student performance on state standardized assessments (for example, on exit exams or state assessments), grade promotion or multiyear credit accrual, and on-time graduation.

Student persistence in school is part of the EWIMS theory of action and was intended to be a main outcome. However, due to limitations with the within-school year enrollment and exit code data available to operationalize persistence, it was more appropriate to present descriptive statistics on preliminary persistence and not treat the study's persistence measure as a primary outcome.

Preliminary persistence was operationalized for the study as enrollment status as of spring 2015, using enrollment status and exit code data collected from states and schools at the end of the 2014/15 school year. These data included the date a student entered the school or school district (entry date), the date a student was no longer enrolled at the school (exit date), and the exit code recording the reason a student withdrew from the school. Enrollment data from both the 2013/14 and 2014/15 school years were combined with 2014/15 outcome data (courses, grades, attendance) to determine whether a student was enrolled in school at the end of the 2014/15 year. Using the data available at the end of the 2014/15 school year, preliminary persistence was operationalized in the following way:

- Students with exit codes indicating that the students were enrolled in a school were coded as 1.
- Students with exit codes indicating that the students left and did not reenroll in any school were coded as 0.
- Students with exit codes indicating that the students transferred out of the country or to other schools, either in- or out-of-state, with no transcript requests from the new schools, were coded as having an unclear enrollment status (as were students who had an exit code of homeschooled[17] or deceased or who had an exit date prior to the end of the school year but who were missing an exit code).

Table C8. Coding of outcome variables for the 2014/15 school year data

Outcome	Coded values	Coding description
Short-term binary risk indicators		
Chronic absence	1 = missed 10 percent or more of enrolled school days, 0 = did not miss more than 10 percent of enrolled school days	The total number of days/hours/periods a student was absent during the 2014/15 school year was divided by the total number of days/hours/periods a student was enrolled during the school year to calculate the percentage of instructional time a student missed. Percentages greater than or equal to 10 percent were coded as 1, and percentages less than 10 percent were coded as 0. Students with an exit code that clearly indicated dropout and missing data for the chronic absence outcome were coded as 1.
Course failure (failing any course)	1 = failed one or more courses, 0 = did not fail any courses	Course grades for all attempted semester-long, trimester-long, or yearlong courses during the 2014/15 school year were coded, and students who received one or more F's or E's were coded as 1. Students who did not receive any F's or E's were coded as 0. Students with an exit code that clearly indicated dropout and missing data for the course failure outcome were coded as 1.
Low grade point average (GPA)	1 = GPA of 2.0 or lower, 0 = GPA above 2.0	Cumulative GPAs on a 4.0 scale were recoded into a binary variable where GPAs lower than or equal to 2.0 were coded as 1 and GPAs higher than 2.0 were coded as 0. Four schools (2 EWIMS schools and 2 control schools) used a 12-point GPA scale. GPAs on a 12-point scale were coded as 1 if the GPA was lower than or equal to 6.0, and GPAs above 6.0 were coded as 0. There were no differences in the number of EWIMS and control schools that provided cumulative versus noncumulative GPA data (two EWIMS schools and no control schools provided GPAs only for the 2014/15 school year—that is, noncumulative GPAs). Cumulative and noncumulative GPA values were combined for analyses. Students with an exit code that clearly indicated dropout and missing data for the low GPA outcome were coded as 1.
Suspension	1 = suspended one or more times, 0 = not suspended	Total suspensions during the 2014/15 school year were coded as 1 if the number of suspensions was greater or equal to 1 or if the number of days suspended was greater or equal to 1. Total suspensions included in-school and out-of-school suspensions. Students with zero suspensions or missing information on suspensions were coded as 0 if behavioral data were provided for the school. That is, students missing behavioral data were assumed to have no behavioral incidents, after confirming with schools. Students with an exit code that clearly indicated dropout and missing data for the suspension outcome were coded as 1.
Student progress in school		
Progress	1 = insufficient credits earned, 0 = sufficient credits earned [number of credits needed to graduate divided by two for second-year students and by four for first-year students]	In State 1, first-year students with 10 or more credits and second-year students with 20 or more credits were coded as 0. In State 2, first-year students with 4.5 or more credits and second-year students with 9 or more credits were coded as 0. In State 3, first-year students with five or more credits and second-year students with 10 or more credits were coded as 0. Students in each state and grade below these thresholds were coded as 1. Students with an exit code that clearly indicated dropout and missing data for the progress outcome were coded as 1.

EWIMS is the Early Warning Intervention and Monitoring System.

Source: Authors' compilation.

The data used to operationalize preliminary persistence are potentially incomplete or not fully accurate because schools often report students as still enrolled at the end of the school year even if they have not attended recently and wait to assign a more formal exit code (for example, transfer, dropout) in the fall of the next school year if the student fails to matriculate. Because this study did not follow students through fall 2015, persistence rates in spring 2015 may appear higher than they were and may not yet reflect potential differences by condition. For this reason, findings involving preliminary persistence should be interpreted with caution, and a longer study is needed to more accurately estimate the impact of EWIMS on school persistence. Analyses on preliminary persistence can be found in appendix D (see figure D2).

A longer study is also needed to estimate the impact of EWIMS on dropout rates from year to year, as well as on grade promotion and multiyear credit accrual. Those outcomes that require longitudinal data collection across school years were out of scope for the current study but are acknowledged as critically important outcomes that an intervention like EWIMS intends to positively affect.

Student performance on state standardized tests also was originally intended to be included as a main study outcome. However, because the states involved in the study planned to transition to different state assessments (aligned with the Common Core state standards) in spring 2015, student-level state test scores were not available for use in the study. In addition, only one of the states used exit exams.

Finally, as the purpose of EWIMS is to identify and support at-risk students to help them get on track for on-time graduation, graduation within four years of high school entry is a critical outcome, but it was out of scope for this particular study. As noted in the Implications section and throughout the main report, additional research is needed to document the potential impact of EWIMS on on-time graduation rates.

Impact analyses

Impact analyses of student outcomes. Because the primary outcomes were binary and students were nested in schools, all primary impact models and sensitivity analyses used multilevel logistic regression models. Models assumed a constant treatment effect and included dummy variables to capture the matched pair random assignment. Baseline student demographic and prior achievement characteristics were also included to improve the precision of the treatment estimate. A multilevel logistic regression was used for the binary outcomes with the following formula:

$$\begin{gathered}\eta_{ij} = \gamma_{00} + \gamma_{01}(\text{condition}_j) + \gamma_{02}\Sigma(\text{pair ID dummy variables}_j) + \\ \gamma_{10}\Sigma(\text{student demographic covariates}_{ij}) + \gamma_{20}(\text{grade 8 reading test score}_{ij}) + \\ \gamma_{30}(\text{grade 8 math test score}_{ij}) + \gamma_{40}\Sigma(\text{missing data flags}_{ij}) + u_{0j}\end{gathered}$$

where $\eta_{ij} = \log(\varphi_{ij} / 1 - \varphi_{ij})$ is the log of the odds of the binary outcome of interest. For example, η_{ij} is the log odds of failing a course for student *i* in school *j*, and φ_{ij} is the probability of failing a course. If the probability of failing a course φ_{ij} is 0.5, the odds of failing a course $\eta_{ij} = \log(\varphi_{ij} / 1 - \varphi_{ij}) = 0.5 / 0.5 = 1.0$, and the log-odds (or logit) is log (a) = 0. If the probability of failing a course is less than 0.5, the odds are lower than 1.0 and the logit is negative.

Condition$_j$ is an indicator variable that takes a value of 1 for EWIMS schools and 0 for control schools; γ_{00} represents the log odds of the binary outcome of interest (for example, failing a course) when all covariates are 0; γ_{01} captures the impact of EWIMS (or the difference in log odds of the binary outcome of interest [for example, failing a course] between students in EWIMS schools and control schools, controlling for all student and school covariates); γ_{02} represents the vector of coefficients for the matched pair dummy indicators; γ_{10} represents the vector of coefficients for the student demographic characteristics (including age, gender, racial/ethnic minority status, special education status, English learner status, and grade); γ_{20} and γ_{30} represent students' prior achievement on state math and reading tests; γ_{40} represents the vector of coefficients for the missing data flags; and u_{0j} is the error term for school j.

Standardized differences for binary outcomes are measured using the Cox index effect size. Cox index effect sizes are standardized differences in the probability of the occurrence of an event. They yield effect size values similar to the values of Hedges' *g* that one would obtain if group means, standard deviations, and sample sizes were available, assuming the dichotomous outcome measure is based on an underlying normal distribution.

Sensitivity analyses. In addition to estimating the primary impact models just described, the study conducted sensitivity analyses using different combinations of the student-level covariates, different strategies to adjust for missing data, and different specifications of the outcome variables. Sensitivity analyses included the following:

- A set of models that excluded all student covariates but retained the dummy variables for school matched pairs and the treatment indicator.
- A set of models that excluded all student covariates, with the exception of the standardized grade 8 state reading and math test scores and the missing data flags for these two prior achievement measures but retained the dummy variables for school matched pairs and the treatment indicator.
- A set of models that contained the same covariates as the primary impact model and used listwise deletion instead of dummy variable covariate adjustment for missing data.
- A set of models that contained the same covariates as the primary impact model and used inverse probability weighting to adjust for missingness.
- A set of models that used a common analytic sample for all outcomes (that is, schools and students with nonmissing outcome data for all outcome measures).
- A set of models that used the continuous variables that were used to create the binary risk indicators (for example, GPA in place of low GPA).

Two additional sensitivity analyses were conducted for specific outcomes. For the course failure primary impact model, one additional sensitivity analysis used a binary indicator of core course failure. For the low GPA primary impact model, one additional sensitivity analysis removed the four schools (and their matched pairs) that used a 12.0 scale for GPA.

For the models that used continuous data rather than the binary risk indicators, linear multilevel regression models were specified. A continuous specification of chronic absence (percentage of instructional time absent), course failure (percentage of courses failed), GPA (on a 4.0 or 12.0 scale, depending on the school), and credits earned were regressed on the same set of covariates included in the primary impact models just discussed. Because four schools calculated GPA on a 12.0 scale rather than a 4.0 scale, the results for GPA were estimated by including a dummy indicator for whether the school had a 12.0 scale or not. These models were estimated using the following equation:

$$Y_{ij} = \gamma_{00} + \gamma_{01}(\text{condition}_j) + \gamma_{02}(\text{pair ID dummy variables}_j) + \\ \gamma_{10}(\text{student demographic covariates}_{ij}) + \gamma_{20}(\text{grade 8 reading test score}_{ij}) + \\ \gamma_{30}(\text{grade 8 math test score}_{ij}) + \gamma_{40}\ (\text{missing data flags}_{ij}) + u_{0j} + r_{ij}$$

Analyses by grade. Subgroup analyses examined whether EWIMS had a different effect for students in grades 9 and 10. These analyses used models that interacted condition with grade level, as displayed in the following model:

$$\eta_{ij} = \gamma_{00} + \gamma_{01}(\text{condition}_j * \text{grade10}_{ij}) + \gamma_{02}(\text{condition}_j * (1\text{-grade10}_{ij})) +$$
$$\gamma_{03}\Sigma(\text{Pair ID dummy variables}_j) + \gamma_{10}\text{student demographic covariates}_{ij}) +$$
$$\gamma_{20}(\text{grade 8 reading test score}_{ij}) + \gamma_{30}(\text{grade 8 math test score}_{ij}) +$$
$$\gamma_{40}\ (\text{missing data flags}_{ij}) + \gamma_{11}(\text{grade10}_{ij}) + u_{0j}$$

where γ_{01} represents the coefficient for the treatment effect for second-year students and γ_{02} represents the coefficient for the treatment effect for first-year students.

Exploratory school data culture analyses. Linear regression models were estimated to analyze the impact of EWIMS on school data culture, both the overall scale score and the school data culture subscales (context for data use, concrete supports for data use, data-driven student support, and barriers to data use). These analyses were considered exploratory because they had limited statistical power to detect an impact of EWIMS at the school level, requiring an effect size of 0.70 or greater. These models included fixed effects for matched pairs, three covariates, and the treatment indicator, as follows:

$$\text{School data culture} = \beta_0 + \beta_1(\text{condition}) + \beta_2(\text{school size}) + \beta_3(\text{on-time graduation rate}) +$$
$$\beta_4(\text{baseline data-driven dropout prevention}) + \beta_5(\text{pair ID Dummy Variables}) + \varepsilon$$

School data culture is the school-level Rasch score on the data culture survey scale. The parameter of interest, β_1, estimates the impact of EWIMS on school data culture. Similar models were run to examine the impact of EWIMS on the four data culture subscales that composed the overall data culture measure. The effect size for each school-level analysis was calculated as Hedges' *g*, which adjusts for small sample sizes.[18]

Implementation analyses

Participation in professional development offered to EWIMS schools. Attendance sheets were used to calculate the percentage of the 37 EWIMS schools that participated in each session (see appendix A).

Level of implementation of the EWIMS seven-step process overall and for each of the seven steps (programmatic implementation). Analysis of the extent and level of implementation of the seven steps of the EWIMS process was based on a rubric that drew on multiple data sources. The rubric measured schools' levels of implementation on each of the seven steps of the EWIMS process and across the seven steps for an overall implementation rating (table C9). To construct the rubric, the EWIMS technical assistance liaisons identified key features of implementing each step; set thresholds for low, moderate, and high levels of implementation on each indicator; and established requirements for achieving low, moderate, or high implementation overall and for each step. The indicators for each step were based on the Early Warning System Implementation Guide developed by the National High School Center (Therriault et al., 2010). To achieve moderate or high implementation scores across steps, the rubric required consistently high or moderate implementation ratings on each of the EWIMS steps, except step 7 (evaluating and refining the EWIMS process).

Table C9. Rubric used to measure implementation during the 2014/15 school year

Step 1: Establish roles and responsibilities			
Step 1 involves organizing the personnel required to employ the process in the school. Schools may construct a new school based team to run EWIMS, or the process may be incorporated into an existing team. The EWIMS team is responsible for implementing the EWIMS process in the school, and EWIMS team members are the recipients of EWIMS training. Ideally, EWIMS team members reflect a range of responsibilities, skill, and knowledge. The team should have the authority to make decisions for the building, and have access to information about individual students. The team is expected to meet regularly (at least monthly) throughout the school year.			
Indicator	“Low” rating definition	“Moderate” rating definition	“High” rating definition
1.1 Champion	No EWIMS champion on team or in the school building.	The team has a champion, but he or she is not empowered to make changes OR The team has an empowered school leader on the team, but this leader is not invested in the EWIMS process.	The team has a champion. This champion has the authority to implement new interventions and make changes within the school building.
1.2 Team membership	The team lacks members with knowledge of interventions and student needs.	The team includes staff members who have knowledge of students or knowledge of interventions available to students.	Team includes staff members with knowledge of students and the interventions available to those students.
1.3 Meeting frequency	The team does not formally meet or holds three or fewer formal EWIMS meetings during the course of the school year.	The EWIMS team holds formal meetings at least every other month (four to seven meetings over the year), and these meetings align to major points in the school calendar.	The EWIMS team holds formal meetings on a monthly basis OR the team holds meetings in every month but one.
Step 1 overall	School receives a “low” rating on at least one indicator.	School receives at least a “moderate” rating on each indicator, but does not do well enough to be rated “high” overall on this step.	School receives “high” ratings on *Champion* and *Team Membership* indicators and no lower than “moderate” on *Meeting Frequency* indicator.
Step 2: Use the early warning data tool			
Step 2 involves the deployment of technology to identify students who are at risk of not graduating high school on time. Staff are expected to import both student- and intervention level data into the tool at prescribed times (before the school year, at the 20- or 30 day mark, at the end of each grading period, and at the end of the year). Staff also should upload and keep updated an inventory of school based interventions, and should use the tool to document the assignment of students to interventions (including start and end dates).			
Indicator	“Low” rating definition	“Moderate” rating definition	“High” rating definition
2.1 Timing of imports	Does not import student data into the early warning data tool.	Imports student data at least once during the school year, apart from the training provided by the EWIMS technical assistance liaisons.	Imports student data into the tool throughout the school year (once in the winter for schools on a semester schedule, once in the winter and spring for schools on trimester schedules).
2.2 Correct and complete data	Does not import student data into the early warning data tool.	Imports student data into the tool, but it is not for the full set of data elements—demographic, attendance, behavior, and academic data.	Imports correct student data into the early warning data tool.
2.3 Tracking interventions	Zero or one interventions have been uploaded into the early warning data tool.	Students are assigned to at least one intervention in the tool, apart from assignments constructed as a part of the early warning data tool training.	Schools use the early warning data tool to assign students to interventions in a systematic manner. Schools may assign interventions at several points during the school year, or the same intervention is updated with different entry and exit dates for students.
Step 2 overall	School receives a “low” rating on at least one indicator.	School receives at least a “moderate” rating on each indicator, but does not do well enough to be rated “high” overall on this step.	School receives a “high” rating on each indicator.

(continued)

Table C9. Rubric used to measure implementation during the 2014/15 school year *(continued)*

Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
Step 3: Review the early warning data			
In step 3, EWIMS teams review data from the early warning data tool to identify students who are not on track for graduation. In addition, the EWIMS team uses the early warning data tool to understand grade- and building level patterns in student risk. Schools should go through step 3 whenever new data are added to the tool.			
Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
3.1 Identification of at-risk students	Team does not use a systematic approach to identify at-risk students.	Team employs a systematic approach to identifying students but uses nonresearch-based thresholds to identify students at risk of not graduating on time (excluding locally validated indicators).	Team uses research-based or locally validated thresholds to identify students at risk of not graduating on time.
3.2 Frequency of student data review	Team reviews student data in fewer than three EWIMS team meetings per school year.	Team reviews student data in three to five EWIMS team meetings per school year.	EWIMS team reviews student data in more than five EWIMS team meetings per school year.
3.3 Reviewing patterns of risk	Does not use early warning system data to explore school- and grade-level patterns of risk.	Uses early warning system data to explore trends and patterns in student risk but does not generate additional questions about student needs.	Uses early warning system data or reports to explore school- and grade-level trends and patterns of risk and uses this data as starting points to generate questions about student needs.
Step 3 overall	School receives a "low" rating on at least one indicator.	School receives at least a "moderate" rating on each indicator, but does not do well enough to be rated "high" overall on this step.	School receives a "high" rating on each indicator.
Step 4: Interpret the early warning data			
In step 4, the EWIMS team moves from *who* is flagged as off track to *why* those students were flagged. Teams engage in the analysis of student data present in the tool and consider information and data from outside of the tool (that is, other teachers, conversations with parents, assessment data) to understand the root causes of students' risk status. The early warning data tool contains reports designed to facilitate this process.			
Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
4.1 Introduce supplemental data	Does not incorporate other information (other data, personal knowledge, other staff) to diagnose student needs.	Uses data and knowledge "in the room" to determine student needs.	Incorporates several sources of additional information to diagnose student needs.
4.2 Understanding underlying causes	Does not examine underlying causes of student risk.	Sometimes examines underlying causes of risk, but this process is not used consistently or is unstructured.	Team uses a systematic process to explore underlying causes of risk for flagged students in order to assign them to the appropriate intervention(s).
Step 4 overall	School receives a "low" rating on at least one indicator.	School receives at least a "moderate" rating on each indicator, but does not do well enough to be rated "high" overall on this step.	School receives a "high" rating on each indicator.

(continued)

Table C9. Rubric used to measure implementation during the 2014/15 school year *(continued)*

Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
Step 5: Assign and provide interventions			
Once the EWIMS team discusses the root causes of flagged students' risk indicators, they should match those students to the intervention or resource that will be best suited to support the students. The school not only should have many different kinds of interventions available to students, but school staff members (especially on the EWIMS team) need to know which interventions will address each student s (or groups of students) needs.			
5.1 Inventory of interventions	School does not have an inventory of interventions.	School has an inventory of interventions, but these interventions do not address all three factors of risk (attendance, behavior, academics).	School has interventions available to students that address all three risk factors.
5.2 Assignment of interventions—frequency	Team does not match students to interventions.	Team matches students to interventions but only at infrequent time points, such as the beginning of the year or the end of grading periods.	Team matches students to interventions on a rolling, as-needed basis.[a]
5.3 Assignment of interventions—coverage	Team matches less than 25 percent of identified at-risk students to interventions.	Team matches 25 percent to 74 percent of identified at-risk students to interventions.	Team matches at least 75 percent of identified at-risk students to interventions.
Step 5 overall	School receives a "low" rating on at least one indicator.	School receives at least a "moderate" rating on each indicator, but does not do well enough to be rated "high" overall on this step.	School receives a "high" rating on *Inventory of interventions* and *Assignment of interventions—frequency*, and at least a "moderate" rating on *Assignment of interventions—coverage.*
Step 6: Monitor students			
Once the EWIMS team has assigned students to interventions, the team should track those students' progress in those interventions. The team examines whether students appear to be responding positively to the intervention (and moving toward being on track) or if the intervention does not appear to be working. In addition, the team monitors student progress to consider the overall effectiveness of interventions.			
Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
6.1 Track student progress in interventions	School does not monitor student progress in interventions, and assignment remains static.	Team monitors student progress in interventions and decides whether to continue placement or modify the assignment, but the decision does not incorporate data.	Team monitors student progress on an ongoing basis (at least monthly) and incorporates data into the decision whether to continue or modify the intervention assignment.[b]
6.2 Monitor effectiveness of interventions	School does not consider modifying intervention inventory.	School modifies interventions without using data to consider effectiveness of those interventions OR School uses data to consider intervention effectiveness but does not make changes to intervention inventory.	School uses data to consider the effectiveness of interventions and may add, eliminate, or modify those interventions.
Step 6 overall	School receives a "low" rating on at least one indicator.	School receives at least a "moderate" rating on each indicator, but does not do well enough to be rated "high" overall on this step.	School receives a "high" rating on each indicator.

(continued)

Table C9. Rubric used to measure implementation during the 2014/15 school year *(continued)*

Indicator	"Low" rating definition	"Moderate" rating definition	"High" rating definition
Step 7: Evaluate and refine the early warning data process			
Step 7 involves EWIMS team reflection about successes and challenges related to the previous six steps. The team should understand its current strengths and weaknesses and create documented plans for improvement. At the conclusion of the school year, the team should ensure a process is in place to transition to the next fall.			
7.1 Reflection on team progress	The team has not identified successes or challenges that emerged from their school's EWIMS process.	The team has identified challenges to the EWIMS process, but has not identified clear action steps to address these challenges.	The team has identified challenges and clear action steps to address these challenges in the coming school year OR The team has already begun to implement changes to address challenges.
Step 7 overall	School receives a "low" rating.	School receives a "moderate" rating.	School receives a "high" rating.
Overall implementation rating			
	"Low" rating definition	"Moderate" rating definition	"High" rating definition
Overall implementation	School does not receive moderate or high overall rating.	School receives at least a "moderate" rating on steps 1 through 6 but can have a "low" rating for step 7.	School receives a "high" rating on steps 1 through 6 but can have a "moderate" rating for step 7.

EWIMS is the Early Warning Intervention and Monitoring System.

Note: "Research-based" for the purposes of this study was defined as schools using the indicators and thresholds preloaded into the tool to identify students at risk for not graduating on time. However, in other contexts, "research-based" could include locally validated indicators or thresholds based on historical data for that specific school or for similar schools, districts, or states. In interviews with EWIMS schools and the EWIMS meeting logs, EWIMS schools were asked to explain how they identified students at risk for not graduating on time, and some schools said they primarily used their own data or thresholds to identify students. Many of the schools in this group examined similar kinds of data (attendance records, behavior reports, and course failure reports), but they relied on past experience to decide which students to identify as at-risk students and assign them to interventions. A third group of schools relied exclusively on non-data-based sources (such as teacher referral) to identify students as at risk. These schools would be rated lower on step 3.1 (identification of at-risk students) because they were not using the research-based indicators from the tool (see table D7 in appendix D for a summary of the ratings on indicator 3.1).

a. Although much of the data in the early warning data tool are refreshed each grading period, students could be assigned to new interventions on an as-needed basis based on attendance data, interim grades, or conversations with the student, family, or other school staff. Also, new students may enter the school who need to be assessed and assigned to interventions.

b. EWIMS teams may monitor student progress in interventions using interim data, such as attendance reports, progress reports, or grades on tests or coursework, or they may regularly check in with students or school staff who work with those students.

Source: Authors' compilation.

The rubric was developed by the EWIMS technical assistance liaisons for the purpose of this project, but with full implementation of the model in mind. EWIMS is designed to be a multiyear continuous improvement process; therefore, many schools will not achieve high implementation of the full seven-step model in one year. For the study, placing EWIMS schools on a continuum reflecting a conceptualization of "full" implementation of the model was believed to most appropriately contextualize the impact analyses.

To develop ratings for each EWIMS school in the study, two evaluators independently rated each school on all indicators within and across the seven steps by analyzing all available data that were collected from EWIMS schools, extant documents on EWIMS implementation from the EWIMS technical assistance liaisons, monthly logs of EWIMS meetings, early warning data tool reports that captured tool use, and interviews with EWIMS team members conducted in spring 2015.[19]

Coders first independently coded each school and then met on a weekly basis to share their ratings, reconcile any discrepancies, and come to a consensus on a final implementation score for each indicator and corresponding step.

Barriers to implementation. To document the challenges that EWIMS schools faced in their first year of adoption, the study used the customized support plans and summaries that the EWIMS technical assistance liaisons created for each school. One analyst coded the customized support plans. Two analysts coded the school summaries, with each coding half of the summaries independently. These codes were developed iteratively based on themes that emerged regarding challenges (for example, compatibility between schools' student information system and early warning data tool, schools' capacity to manage and use data, schools' ability to upload complete and accurate data to the tool, schools' ability to use the tool's intervention function, and challenges stemming from the amount of time it took to use the tool). Information from exit interviews from seven of the eight schools that stopped or never began implementing EWIMS also were used to describe the barriers.

Specific types of interventions used by EWIMS schools and student assignment to interventions. To catalog the types of interventions offered in schools using EWIMS, the study used information from three data sources: the school leader surveys from spring 2014 and 2015,[20] the early warning data tool reports, and the EWIMS team interviews. Interventions extracted from each data source were combined into one file, and duplicate interventions represented across multiple data sources for a school were removed. Each intervention was then coded by area of risk (chronic absence, behavior, course failure, and multidomain) and then by type of intervention (for example, academic support, mentoring, truancy, tutoring, and parent conference; see table D9 in appendix D).

To examine the match between student indicators of risk and the interventions assigned to students, the study used data from the early warning data tools. Specifically, the number and percentage of students at risk because of chronic absence, course failure, or behavioral problems—or because of multiple risk indicators that were assigned to any intervention categorized as addressing those particular issues—were calculated.

Treatment contrast. These analyses used items from the 2014/15 end-of-year school leader survey that asked about use of an early warning system, the presence of a dedicated team to identify and support at-risk students, the frequency of data review, and the number and type of interventions. Responses to the survey were analyzed descriptively (the number and percentage of schools selecting each response option). To test the difference between EWIMS and control schools on measures of aspects of EWIMS implementation, a mix of logistic and linear regression models was conducted. The linear and logistic regressions for all treatment contrast analyses included three covariates—school size, on-time graduation rate, and baseline data-driven dropout prevention efforts. Linear regression also included dummy variables for matched pairs, but the logistic regressions do not include these variables due to perfect prediction between the pair ID and binary outcomes.

To measure whether schools adhered to their randomly assigned groups, the survey asked school leaders whether they used an early warning system during the 2014/15 school year; logistic regressions were run using binary indicators of whether or not a school reported having an early warning system. Logistic regressions were also run with a binary indicator of whether or not a school reported having a dedicated team to identify and support at-risk students. For the frequency of data review, logistic regressions were analyzed that used a binary indicator of whether or not schools reviewed attendance or course failure data at least monthly as the outcome. For the number of interventions, linear regressions were run that used the sum of the number of interventions reported on the school leader survey as the outcome. For type of interventions, logistic regressions were run using a binary indicator of whether a school offered each type of intervention (attendance intervention, academic intervention, or behavioral intervention) as the outcome.

Appendix D. Detailed findings and supplementary analyses

This appendix contains detailed findings related to the analyses presented in the main body of the report as well as supplementary analyses not included in the main body of the report. The analyses presented in this appendix include the following:

Impact findings

- Detailed findings from the main impact models and sensitivity analyses used to test whether the main impacts are robust to different model specifications for chronic absence, course failure, low grade point averages (GPA), suspensions, and progress in school.
- Sensitivity analyses used to examine whether the impact of the Early Warning Intervention and Monitoring System (EWIMS) on continuous outcomes is consistent with the main impact analyses of binary outcomes.
- Detailed findings for the exploratory analyses used to test whether the impact of EWIMS differed by grade (first-year students versus second-year students).
- Supplementary analysis of the preliminary persistence measure.
- Detailed findings for the exploratory analyses of school data culture.

Implementation findings

- Detailed findings on satisfaction with EWIMS training.
- Detailed findings for the level of implementation.
- Supplementary findings for the barriers experienced by schools that stopped or never began implementing EWIMS.
- Detailed findings for the percentage of students flagged in the early warning tools.
- Detailed findings for the specific types of interventions offered in EWIMS schools.
- Detailed findings for the treatment contrast analyses.

Detailed findings from the main impact models and sensitivity analyses used to test whether the main impacts are robust to different model specifications for chronic absence, course failure, low GPA, suspension, and progress in school

Sensitivity analyses examined whether the impact estimates reported in the main body of the report were robust across different specifications of the impact models (tables D1 and D2). The sensitivity analyses suggest that the estimated impact of EWIMS on students is stable in magnitude, direction, and statistical significance, regardless of model specification for all student outcomes.

Sensitivity analyses examining the impact of the Early Warning Intervention and Monitoring System on continuous rather than binary outcomes

In addition to the sensitivity analyses that used alternate specifications of the analysis models, models were also analyzed that used the continuous specification of the binary outcomes. The continuous outcomes were the percentage of instructional time missed, the percentage of courses failed, GPA, and credits earned. In some cases, the student sample size for these models was larger than that used for the primary impact model because the models with continuous outcomes did not drop cases due to perfect prediction (see note in table D1).

Table D1. Results from main analyses and sensitivity models for chronic absence, course failure, low GPA, suspension, and progress in school in 2014/15

Model	Predicted probability for treatment	Predicted probability for control	Odds ratio	Standard error	*p*-value	Cox index effect size	Student sample size	School sample size
Outcome: Chronic absence (missed 10 percent or more of instructional time)								
1	0.10	0.14	0.66	0.07	<.001	–0.26	35,876	65
2	0.11	0.15	0.70	0.08	.001	–0.21	35,888	65
3	0.10	0.14	0.66	0.07	<.001	–0.25	35,888	65
4	0.09	0.12	0.77	0.08	.013	–0.16	25,732	62
5	0.08	0.11	0.65	0.08	.001	–0.26	35,876	65
6	0.09	0.14	0.64	0.07	<.001	–0.28	26,976	52
Outcome: Course failure (one or more course failures)								
1	0.21	0.26	0.76	0.06	<.001	–0.17	35,133	65
2	0.26	0.30	0.81	0.06	.002	–0.13	35,133	65
3	0.22	0.27	0.76	0.06	<.001	–0.17	35,133	65
4	0.20	0.24	0.81	0.06	.008	–0.13	25,294	62
5	0.14	0.18	0.75	0.07	.002	–0.17	35,133	65
6	0.21	0.26	0.73	0.07	.001	–0.19	26,976	52
7	0.20	0.24	0.77	0.06	.001	–0.16	35,133	65
Outcome: Low grade point average (2.0 or lower)								
1	0.17	0.19	0.87	0.08	.122	–0.09	30,080	57
2	0.24	0.26	0.91	0.08	.278	–0.06	30,086	57
3	0.18	0.20	0.86	0.08	.087	–0.09	30,086	57
4	0.15	0.16	0.97	0.09	.731	–0.02	21,506	54
5	0.15	0.17	0.86	0.08	.090	–0.09	30,080	57
6	0.16	0.18	0.89	0.09	.249	–0.07	26,976	52
7	0.17	0.19	0.85	0.08	.098	–0.10	26,829	51
Outcome: Suspension (suspended one or more times in the 2014/15 school year)								
1	0.09	0.09	0.91	0.13	.497	–0.06	35,501	63
2	0.11	0.12	0.93	0.13	.567	–0.05	35,558	63
3	0.09	0.10	0.91	0.13	.497	–0.06	35,558	63
4	0.08	0.08	1.10	0.15	.474	0.06	25,960	61
5	0.08	0.09	0.89	0.13	.423	–0.07	35,501	63
6	0.09	0.10	0.87	0.15	.420	–0.08	26,976	52
Outcome: Progress in school (credits earned)								
1	0.14	0.14	0.98	0.23	.913	–0.02	35,044	63
2	0.17	0.17	1.01	0.19	.967	0.01	35,050	63
3	0.14	0.15	0.97	0.22	.878	–0.02	35,050	63
4	0.13	0.13	1.00	0.21	.998	<0.00	24,949	59
5	na	na	na	na	na	na	na	na
6	0.09	0.09	1.07	0.20	.704	0.04	26,976	52

na is not applicable because the model with inverse probability weights did not converge for progress in school.

Note: *Model 1* is the primary impact model: a multilevel logistic regression with students at level 1 and schools at level 2, including binary indicators for student demographic covariates and grade, the grade 8 standardized tests in reading and math, missing data flags for each covariate, a set of dummy variables that captures school matched pairs, and the treatment indicator, which identifies schools as EWIMS schools or control schools. *Model 2* has the same functional form as Model 1 but excludes all student covariates. *Model 3* has the same functional form as Model 1 but excludes all student covariates except the pretests—the grade 8 standardized tests in reading and math and the missing data flags for these two pretest measures—and retains the dummy variables for school matched pairs and the treatment indicator. *Model 4* has the same functional form as Model 1 and includes all of the covariates included in the primary impact model but uses listwise deletion for missing data on the covariates. *Model 5* has the same functional form as Model 1 and includes all of the covariates included in the primary impact model but uses inverse probability weighting to correct for missingness on the outcome. *Model 6* has the same functional form as Model 1 but only includes students with nonmissing outcome data for all outcome measures. *Model 7* for course failure uses the same functional form and covariates as Model 1 but uses a binary measure of core course failure (1 = failed a core course, 0 = did not fail a core course) as the outcome measure instead of a binary measure of course failure. *Model 7* for low GPA uses the same functional form and covariates as Model 1 but excludes schools and their matched pairs where GPA was reported on a 12.0 scale. The student analytic sample for Model 1 is smaller than the total student sample by 12 observations for chronic absence, 6 observations for low GPA, 57 observations for suspensions, and 6 observations for progress. These differences in sample sizes occurred because students are dropped due to perfect prediction between covariates and outcomes in the statistical analyses in Model 1. Model 2 excludes the covariates and thus avoids losing observations due to perfect prediction during estimation.

Source: Authors' analysis based on extant student records described in appendix C.

Table D2. Results of sensitivity models with continuous versions of the outcome variables for chronic absence, course failure, grade point average, and progress in school in 2014/15

Continuous specification	Adjusted means: EWIMS schools	Adjusted means: Control schools	Standard error	*p*-value	Hedges' *g* effect size	Student sample size	School sample size
Student risk indicators							
Chronic absence (percentage of instructional time missed)	5.4	6.5	0.003	.003	–0.12	35,888	65
Course failure (percentage of courses failed)	8.0	9.6	0.005	.004	–0.08	35,133	65
Grade point average	2.98	2.87	0.041	.006	0.07	30,086	57
Student progress in school							
Credits earned	13.05	13.01	0.382	.902	–0.006	35,050	63

Note: Estimates shown were produced using a multilevel regression model with students at level 1 and schools at level 2. The continuous outcomes were regressed on binary indicators for student demographic covariates and grade, the grade 8 standardized tests in reading and math, missing data flags for each covariate, a set of dummy variables that captures school matched pairs, and the treatment indicator, which identified schools as EWIMS schools or control schools. Sensitivity analyses that used the continuous data instead of a binary flag for suspensions could not be conducted because some schools provided data on the number of days suspended, while others provided data on the number of suspensions. Schools did not always clarify whether the suspension data was reported in terms of days or incidents.

Source: Authors' analysis based on extant student records described in appendix C.

These analyses are displayed in table D3 and summarized as follows:

- The average percentage of instructional time missed was significantly lower for students in EWIMS schools than for students in control schools. This is consistent with the main impact analysis showing that EWIMS had an impact in the same direction on the binary indicator of chronic absence.
- The average percentage of courses failed out of those attempted was significantly lower for students in EWIMS schools than for students in control schools; this too is consistent with the main impact analysis showing an impact in the same direction on the binary indicator of course failures.
- Average GPA was statistically significantly higher for students in EWIMS schools than for students in control schools; this finding is inconsistent with the main impact analysis showing no statistically significant effect on the binary indicator of low GPA. A model excluding students at schools or the matched pairs of schools that used a 12.0 scale for GPA was also run to test the sensitivity of the results. The results of this model indicated that the adjusted mean for students in EWIMS schools was 2.72 and for students in control schools was 2.65 (SE = 0.04, *p*-value = .07, Hedges' *g* effect size = 0.07, student sample = 26,836, school sample = 51).
- The average number of credits earned was not statistically significantly different for students in EWIMS schools than for students in controls schools; this finding is consistent with the main impact analyses on student progress in school.

Detailed findings for the exploratory analyses used to test the impact of the Early Warning Intervention and Monitoring System for first-year and second-year students

Results from analyses of the differential impact of EWIMS on the main student outcomes showed that the impact of EWIMS on chronic absence and course failure was larger for

Table D3. The impact of the Early Warning Intervention and Monitoring System on all binary outcomes for first-year and second-year students in 2014/15

Outcome	Predicted probability								
	EWIMS first year	Control first year	EWIMS second year	Control second year	*p*-value	First year sample	Second year sample	Total student sample	School sample
Student risk indicators									
Chronic absence	0.085	0.135	0.126	0.172	.027	18,359	17,517	35,876	65
Course failure	0.246	0.324	0.299	0.350	.011	18,114	16,989	35,133	65
Low GPA	0.198	0.209	0.211	0.231	.292	15,269	14,811	30,080	57
Suspended	0.092	0.094	0.084	0.088	.559	18,104	17,397	35,501	63
Student progress in school									
Progress in school	0.124	0.120	0.132	0.135	.727	18,025	17,019	35,044	63

EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: The predicted probabilities in the treatment and control groups for students by grade were produced using a multilevel logistic regression model with students at level 1 and schools at level 2. Outcomes were regressed on binary indicators of student demographic covariates and grade, the grade 8 standardized tests in reading and math, missing data flags for each covariate, a set of dummy variables that capture school matched pairs, an interaction term between the treatment indicator and an indicator of being a second-year student, and an interaction term between the treatment indicator and an indicator of being a first-year student. The p-value corresponds to a test of the null hypothesis that these two interaction terms are not different or, in other words, that the treatment impact is not different for first- and second-year students. The student analytic samples for chronic absence, low GPA, suspended, and progress in school are the same as those listed for Model 1 in table D1 for each respective outcome. Less than 1 percent of students were dropped due to perfect prediction between covariates and outcomes in the statistical analyses.

Source: Authors' analysis based on extant student records described in appendix C.

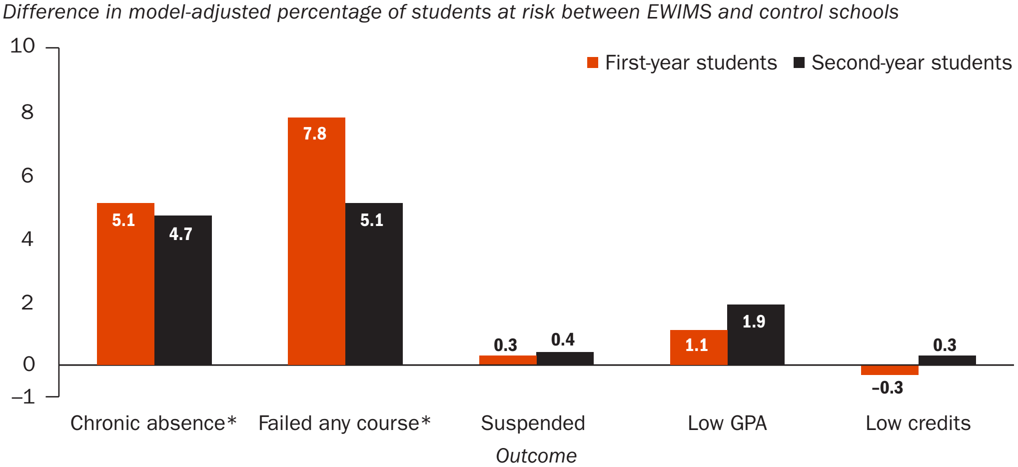
first-year students than for second-year students; there were no differential effects on the other outcomes (see table D2). The difference between EWIMS and control schools in the percentage of students at risk of not graduating on time due to chronic absence was 5.0 percentage points for first-year students and 4.6 percentage points for second-year students. This difference is of little practical importance (about 5 percent for both), but was statistically significant. The difference between EWIMS and control schools in the percentage of students failing one or more courses was 7.8 percentage points for first-year students and 5.1 percentage points for second-year students (figure D1).

Supplementary analysis of the preliminary persistence measure

Analysis of persistence in school was not considered a primary student outcome due to limitations of the enrollment and exit code data available for the study (see "Outcomes not measured or measured with limitations" in appendix C). According to the enrollment and exit code data available at the end of the 2014/15 school year, 95 percent of students in both EWIMS and control schools persisted through the end of the 2014/15 school year. Only about 1 percent of students were recorded as having dropped out of high school before the end of the 2014/15 school year, both in the EWIMS and control schools. The remaining 4 percent of students had unclear enrollment status (figure D2).

Exploratory analyses that tested the difference between the percentage of students who were still enrolled and those who had dropped out (and excluded students with unclear

Figure D1. The impacts of the Early Warning Intervention and Monitoring System on chronic absence and course failure were larger for first-year students than second-year students at the end of the 2014/15 school year



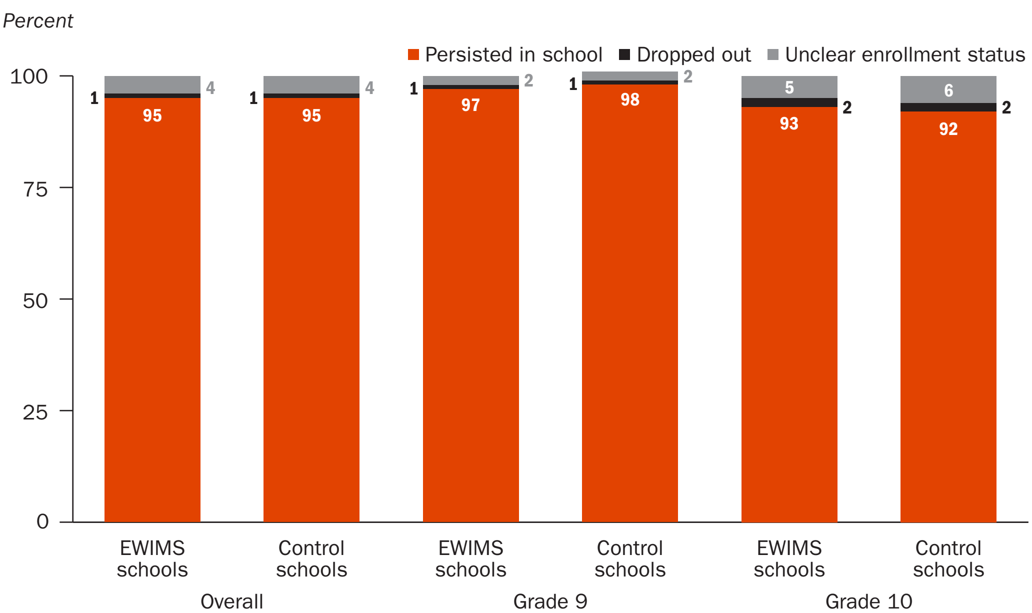
* difference in the estimated impacts for first-year and second-year students was statistically significant at the $p < .05$ level.

EWIMS is the Early Warning Intervention and Monitoring System. GPA is grade point average.

Note: Sample included 65 schools and 35,876 students for chronic absence, 65 schools and 35,133 students for failed any course, 57 schools and 30,080 students for low GPA, and 63 schools and 35,501 students for suspended. See table D3 for more information about these sample sizes.

Source: Authors' analysis based on extant student records from schools, school districts, and state education agencies described in appendix C.

Figure D2. Percentage of students still enrolled, not enrolled, and with unclear enrollment status at the end of the 2014/15 school year



EWIMS is the Early Warning Intervention and Monitoring System.

Note: The bar for control schools in grade 9 does not sum to 100 percent because of rounding. In this bar, 97.63 percent of grade 9 students in control schools persisted, 0.61 percent did not persist, and 1.76 percent had an unclear enrollment status.

Source: Authors' analysis based on extant student records described in appendix C.

enrollment status) showed there was no difference in preliminary persistence between EWIMS and control schools (table D4). Again, due to the enrollment and exit code data limitations, results on student preliminary persistence should be interpreted with caution.

In addition to the impact model described in the previous paragraph, a model that included an interaction between the treatment condition indicator and the indicator of grade was analyzed. The interaction term in this model was not statistically significant (*p*-value = .461), indicating that there was no differential impact of being in an EWIMS school on preliminary persistence by grade.

Detailed findings for the exploratory school data culture analyses

EWIMS had no detectable impact on school data culture (table D5).

The school data culture analyses were conducted on the full sample of schools that responded to the school survey (n = 66). As a sensitivity check, the school data culture analyses were run with a restricted sample that only included matched pairs in each of the analytic samples (the samples for chronic absences, course failure, low GPAs, suspensions, and progress in school). The sensitivity checks were consistent and revealed no change in direction or statistical significance in the school data culture findings, confirming that there was no detectable impact on school data culture.

Detailed findings on satisfaction with Early Warning Intervention and Monitoring System training

Satisfaction surveys were collected after each training to document satisfaction with EWIMS implementation. Overall, satisfaction was high across all trainings. More than 90 percent of respondents were either satisfied or very satisfied with each training (table D6).

Detailed findings for the level of implementation

Only two schools achieved moderate or high overall implementation. However, some schools achieved moderate or high scores for individual steps or on individual indicators within steps (table D7). More than 50 percent of schools achieved high ratings on

Table D4. The impact of the Early Warning Intervention and Monitoring System on preliminary persistence in the 2014/15 school year

Predilcted probability for EWIMS	Predicted probability for control	Odds ratio	Standard error	p–value	Cox index effect size	Student sample size	School sample size
0.99	0.99	0.83	0.10	.123	–0.11	33,124	59

EWIMS is the Early Warning Intervention and Monitoring System.

Note: Estimates shown were produced using a multilevel logistic regression model with students at level 1 and schools at level 2. The binary indicator of preliminary persistence was regressed on binary indicators for student grade, a set of dummy variables that captures school matched pairs, and the treatment indicator, which identified schools as EWIMS schools or control schools. This model specification does not match that of the primary impact models (see table D1) because the model that used preliminary persistence as an outcome did not converge when additional student demographic covariates and student test scores were included due to perfect prediction.

Source: Authors' analysis based on extant student records described in appendix C.

Table D5. The impact of the Early Warning Intervention and Monitoring System on school data culture during 2014/15

Characteristic	EWIMS schools			Control schools			Standardized difference (Hedges g)[a]	p-value
	n	Mean	Standard deviation	*n*	Mean	Standard deviation		
Overall data culture	32	2.92	0.44	34	2.81	0.37	0.27	.301
Dimensions of data culture								
Context for data use	33	2.74	0.41	34	2.75	0.38	–0.02	.947
Concrete supports for data use	32	2.85	0.53	34	2.74	0.46	0.22	.418
Data-driven student support	32	3.06	0.55	34	2.90	0.47	0.31	.196
Lack of barriers to data use[b]	32	2.82	0.56	34	2.72	0.46	0.19	.424

EWIMS is the Early Warning Intervention and Monitoring System. *n* is the number of schools.

Note: Sample included 66 schools that completed the school leader surveys. Data culture items were measured on a 1-to-4 scale, with 1 being low data culture and 4 being high data culture. Regression models that regressed data culture on treatment status, a set of three covariates (school size, baseline on-time graduation rate, and baseline data-driven dropout prevention efforts), and a set of variables capturing school matched pairs revealed no statistically significant differences at the $p < .05$ level.

a. Hedges' *g* is used as the standardized difference to account for small sample sizes. None of the differences was statistically significant at the $p < .05$ level.

b. The items that compose the scale for barriers to data use were reverse coded, such that a higher score indicated fewer barriers.

Source: Authors' analysis based on school leader survey administered in spring 2015.

Table D6. Participant satisfaction with Early Warning Intervention and Monitoring System trainings during 2013/14 and 2014/15

Training	Not satisfied		Satisfied		Very satisfied	
	Number	Percent	Number	Percent	Number	Percent
Regional training	4	2.3	99	57.2	38	39.3
Early warning data tool training	1	1.3	27	34.6	50	64.1
Early warning data tool refresher	3	6.7	13	28.9	29	64.4
Site Visit 1	2	1.6	44	34.1	82	63.5
Site Visit 2	0	0.0	31	37.0	52	63.0
Site Visit 3	3	3.0	41	38.0	64	59.0
WebShare 1	3	8.6	25	71.4	7	20.0
WebShare 2	1	4.3	15	65.2	7	30.4
WebShare 3	1	4.2	14	58.3	9	37.5
WebShare 4	2	9.5	10	47.6	9	42.9
WebShare 5	0	0.0	12	52.2	11	47.8

Note: No respondents chose the lowest option, 'Not at all satisfied,' on any of the satisfaction surveys. Two participants did not respond to the satisfaction item for regional training, and one participant did not respond to the satisfaction item for site visit 1; therefore, the percentages do not add to 100 percent.

Source: Authors' analysis based on attendance sheets from the 2013/14 and 2014/15 trainings.

six indicators, including 89 percent of schools on the indicator related to EWIMS team composition.

Although few schools achieved high overall implementation in the 2014/15 school year, many schools achieved high implementation on individual steps (table D8). Seventy percent of schools achieved high implementation on at least one step, and 24 percent of schools achieved high implementation on at least four steps.

Supplementary findings for the barriers experienced by schools that stopped or never began implementing the Early Warning Intervention and Monitoring System

Eight schools stopped or never began implementing EWIMS during the 2014/15 school year. Exit interviews were conducted with seven of these schools. In these interviews, school staff cited issues related to the early warning data tool as a reason to stop implementation. Staff from four schools said the tool took too long to use, and two schools said they could not access the tool at all. In addition, three schools reported that staff turnover

Table D7. Percentage of Early Warning Intervention and Monitoring System schools that achieved low, moderate, or high implementation ratings during 2014/15, by indicator

	Low score		Moderate score		High score	
Indicator	Number	Percent	Number	Percent	Number	Percent
Overall Implementation	35	95	1	3	1	3
Step 1—Overall	16	43	7	19	14	38
Step 1.1—Champion	13	35	9	24	15	41
Step 1.2—Team membership	2	5	2	5	33	89
Step 1.3—Meeting frequency	10	27	16	43	11	30
Step 2—Overall	6	16	12	32	19	51
Step 2.1—Timing of imports	4	11	6	16	27	73
Step 2.2—Correct and complete data	4	11	5	14	28	76
Step 2.3—Tracking interventions	6	16	9	24	22	59
Step 3—Overall	18	49	15	41	4	11
Step 3.1—Identification of at–risk students	6	16	7	19	24	65
Step 3.2—Frequency of student data review	11	30	15	41	11	30
Step 3.3—Reviewing patterns of risk	14	38	12	32	11	30
Step 4—Overall	8	22	22	59	7	19
Step 4.1—Introduce supplemental data	6	16	5	14	26	70
Step 4.2—Understanding underlying causes	8	22	21	57	8	22
Step 5—Overall	21	57	8	22	8	22
Step 5.1—Inventory of interventions	2	5	17	46	18	49
Step 5.2—Assignment of interventions—frequency	5	14	15	41	17	46
Step 5.3—Assignment of interventions—coverage	20	54	17	46	0	0
Step 6—Overall	21	57	10	27	6	16
Step 6.1—Track student progress in interventions	15	41	8	22	14	38
Step 6.2—Monitor effectiveness of interventions	17	46	12	32	8	22
Step 7—Overall/Reflection on team progress	8	22	11	30	18	49

Note: School *n* = 37, including one school that never implemented EWIMS.

Source: Authors' calculations based on school leader survey, early warning data tool reports, monthly meeting logs, and EWIMS team interviews.

Table D8. Number of steps on which Early Warning Intervention and Monitoring System schools achieved high implementation ratings during 2014/15

Number of steps on which school received "high rating"	Number of schools	Percent
Zero	11	30
One	3	8
Two	9	24
Three	5	14
Four	6	16
Five	2	5
Six	1	3

Note: School *n* = 37, including one school that never implemented the Early Warning Intervention and Monitoring System.

Source: Authors' calculations based on school leader survey, early warning data tool reports, monthly meeting logs, and Early Warning Intervention and Monitoring System team interviews.

contributed to their decision to stop implementing EWIMS, given that they were unable to find replacements for key EWIMS team members. Three schools also said they stopped implementing EWIMS in part because of other school- or district-based initiatives that they perceived to be competing with EWIMS for time and resources. For example, one school identified a new technology initiative as a project that drew technology staff away from supporting EWIMS, while another school said school-based administrators had to devote time to a new educator evaluation system.

Detailed findings for the percentage of students flagged in the early warning tools

For a variety of reasons, the percentages of students flagged in the early warning tools (described on page 14 in the main report) differ from those presented in figure 3 in the main report. First, the percentages reported are based on different samples. In figure 3, the students are those in grades 9 or 10, in either the EWIMS or control group analytic samples, who have complete outcome data. The number of flagged students includes all students in EWIMS schools with data uploaded into the tool, and there were more schools with data in the tools than were included in the impact analyses. Second, the percentages presented in figure 3 are regression-adjusted predicted probabilities from models that include covariates, while on page 14, they are raw percentages. Third, figure 3 presents the percentage of students with each of the indicators across the full year, whereas on page 14, the percentages represent the proportion of students ever flagged over the course of the year in the early warning data tools. This may explain the higher rates of students flagged for attendance and course performance on page 14 than in figure 3.

Detailed findings for the specific types of interventions offered in Early Warning Intervention and Monitoring System schools

To document interventions used in EWIMS schools, researchers extracted and coded information from three different data sources: the school leader surveys from spring 2014 and 2015, the early warning data tool reports, and the EWIMS team interviews. Academic interventions of any type, tutoring, and traditional credit recovery coursework were most common among EWIMS schools (table D9).

Table D9. Number and percentage of Early Warning Intervention and Monitoring System schools that reported having different interventions and supports available for students in the 2014/15 school year

Intervention type	EWIMS schools that reported intervention was available	
	Number	Percent
English language arts support	14	38
Algebra support	13	35
Targeted academic support	12	32
Other math support	9	24
Remediation	2	5
Tutoring	25	68
Afterschool tutoring	13	35
Peer tutoring	7	19
Credit recovery	24	65
Online credit recovery	10	27
Mentoring	23	62
Peer mentoring	11	30
Check and connect	3	8
Meet with students and parents	15	41
Letter or phone call home	14	38
Monitoring	13	35
Counseling	11	30
Student contracts	9	24
Mental and physical health services	9	24
Mental health	5	14
Connecting students to community resources	4	11
Teen pregnancy	2	5
Truancy actions	9	24
Disciplinary action (detention, demerits)	6	16
Freshman transition programs	7	19
Social emotional interventions	5	14
Homework or study space interventions	4	11
Alternative education	3	8
Response to intervention	3	8
Teaching and instruction interventions	2	5
Generic academic intervention	26	70
Other	26	70

EWIMS is the Early Warning Intervention and Monitoring System.

Source: Authors' calculations based on school leader survey, early warning data tool reports, and EWIMS team interviews.

Detailed findings for the treatment contrast analyses

The study used end-of-year survey data to examine the contrast between EWIMS and control schools in the practices they used to identify and support students at risk of not graduating on time. The surveys captured the extent to which schools adhered to their randomly assigned groups (according to self-reports of whether they used an early warning system). The surveys also measured whether schools had a dedicated team to identify and support at-risk students, the frequency of data review, and the number and type of interventions offered to students (see appendix C).

Use of an early warning system. Most EWIMS schools (27) and a few control schools (4) reported using an early warning system to organize their data review and assign students to interventions during the 2014/15 school year (table D10). EWIMS schools were significantly more likely than control schools to report using an early warning system. Of the 66 schools that responded to this item on the school leader survey, 87 percent of EWIMS schools and 10 percent of control schools reported using an early warning system in the 2014/15 school year (see figure 7 in the main report and table D10).

Dedicated team to identify and support at-risk students. EWIMS schools were more likely than control schools to report having a dedicated team to identify and support at-risk students (see figure 7 in the main report and table D10). Three-quarters (76 percent) of EWIMS schools and 40 percent of control schools reported that they had a dedicated team to identify and support at-risk students.

Frequency of data review. Both EWIMS and control schools reported reviewing attendance and course failure data frequently (table D11).

Table D10. The percentages of schools that used an early warning system and had a dedicated school-based team differed by treatment status during 2014/15

Outcome	EWIMS schools	Control school	Odds ratio	Cox index effect size	*p*-value
Use of an early warning system	87	10	60.78	2.49	<.001
Use of a dedicated team to identify and support at-risk students	76	40	4.77	0.95	.006

EWIMS is the Early Warning Intervention and Monitoring System.

Note: The sample for the early warning system item included 66 schools that responded to this item on the school leader surveys (32 EWIMS schools and 34 control schools). The sample for the "dedicated team to identify and support at-risk students" item included the 65 schools that responded to this item on the school leader survey (31 EWIMS and 34 control schools). The percentages represent predicted probabilities from logistic regression models that regressed a binary indicator of whether or not a school used an early warning system or had a dedicated team to identify and support at-risk students on treatment status and a set of three covariates (school size, baseline on-time graduation rate, and baseline data-driven dropout prevention efforts). The odds ratios and *p*-values come from these same regression models.

Source: Authors' analysis of school leader survey.

Table D11. Frequency of attendance and course failure data review, as reported on the school leader survey at the end of the 2014/15 school year (percentage of schools)

Outcome	Weekly or more often	Monthly	4 times per year	3 times per year	2 times or less per year
Attendance review in EWIMS schools	38	38	14	7	3
Attendance review in control schools	38	48	10	0	3
Course failure data review in EWIMS schools	21	31	31	7	10
Course failure data review in control schools	19	26	35	6	13

EWIMS is the Early Warning Intervention and Monitoring System.

Note: Sample includes 60 schools that responded to these two items on the school leader survey (29 EWIMS and 31 control schools).

Source: Authors' calculations based on school leader survey.

Table D12. Statistical analyses of the frequency of attendance and course failure data review between Early Warning Intervention and Monitoring System and control schools, as reported on the school leader survey at the end of the 2014/15 school year

Outcome	EWIMS schools (percentage)	Control school (percentage)	Odds ratio	Cox index effect size	*p*-value
Reviewed attendance data at least monthly	76	88	0.44	–0.50	.248
Reviewed course failure data at least monthly	53	42	1.52	0.25	.454

EWIMS is the Early Warning Intervention and Monitoring System.

Note: Sample includes 60 schools that responded to these two items on the school leader survey (29 EWIMS and 31 control schools). The percentages represent predicted probabilities from logistic regression models that regressed a binary indicator of whether or not a school reviewed data at least monthly on treatment status and a set of three covariates (school size, baseline on-time graduation rate, and baseline data-driven dropout prevention efforts). The odds ratios and *p*-values come from the same regression models.

Source: Authors' calculations based on school leader survey.

Models that tested the difference between the percentage of EWIMS and control schools that reviewed attendance and course failure data at least monthly revealed no statistically significant difference in the frequency of data review (table D12).

Number of interventions. There were no statistically significant differences between EWIMS schools and control schools in the reported number of interventions available to support students (EWIMS schools mean [M] = 2.75, standard deviation [SD] = 2.21; control schools [M] = 2.20, [SD] = 2.20, $\beta = 0.55$, SE = 0.58, $p = .358$, Hedges' $g = 0.29$).

Type of interventions. The study examined whether EWIMS schools were more likely than control schools to offer at least one intervention in each of the three domains in which students can be flagged as at risk: chronic absence, course failure, and behavior. Survey responses indicated that a similar percentage of EWIMS and control schools offered interventions in each domain (table D13). Also, because there were so few attendance and

Table D13. The number of schools offering each type of intervention, by condition, during the 2014/15 school year

Outcome	EWIMS schools (percentage)	Control school (percentage)	Odds ratio	Cox index effect size	*p*-value
Attendance intervention	11	9	1.18	0.10	.850
Behavioral intervention	16	9	1.85	0.37	.459
Course performance intervention	96	100	0.00	na	.997

na is not applicable because the Cox index effect size was not calculated for course performance interventions, given that the odds ratio was zero and the natural log of the odds ratio (used to calculate the Cox index effect size) would create an uninterpretable value.

Note: Sample includes 59 schools that responded to these items on the school leader survey (28 EWIMS and 31 control schools). The percentages represent predicted probabilities from logistic regression models that regressed a binary indicator of whether or not a school offered each type of intervention on treatment status and a set of three covariates (school size, baseline on-time graduation rate, and baseline data-driven dropout prevention efforts). The odds ratios and *p*-values come from these same regression models.

Source: Authors' analysis of school leader survey.

behavior interventions reported in the school survey, only five schools offered at least one intervention in all three domains and there was no difference between the number of EWIMS and control schools that offered supports for students in all three domains.

The treatment contrast analyses were conducted on the full sample of schools that responded to the school survey (*n* = 66). As a sensitivity check, models were also run with a restricted sample that only included matched pairs (for chronic absence, course failure, low GPAs, suspensions, and progress in school) in each of the analytic samples. The sensitivity checks were consistent and revealed no change in direction or statistical significance in the treatment contrast analyses.

Appendix E. Disclosure of potential conflicts of interest

The following section discloses any potential conflicts of interest for the Regional Educational Laboratory (REL) Midwest study team in its evaluation of the Early Warning Intervention and Monitoring System (EWIMS). EWIMS was originally developed by American Institutes for Research under a cooperative agreement with the U.S. Department of Education to operate the National High School Center. American Institutes for Research conducted the evaluation of EWIMS as part of its work with REL Midwest's Dropout Prevention Research Alliance.

To conduct the study, REL Midwest established a conservative firewall between implementation of the EWIMS model and its evaluation through the use of two separate teams: an implementation team and an evaluation team. The evaluation team collected all outcome data and analyzed all data for the report. The implementation team worked directly with the EWIMS schools to implement the intervention, including providing training and technical assistance. The implementation team did help facilitate data collection in the EWIMS schools, such as collecting sign-in sheets at professional development sessions, providing links to satisfaction surveys, and reminding school staff to submit administrative data to the evaluation team. However, the implementation team was not involved in any data collection in control schools nor in any analysis or reporting tasks. Furthermore, the evaluation team did not share any data or results with the implementation team during the implementation period other than the data that the team would have collected during typical implementation of EWIMS (for example, results from post-training satisfaction surveys). The evaluation team did not share any findings from the impact analyses with the implementation team until the implementation period for the year of evaluation (2014/15) had ended.

In addition, the report authors and their potential conflicts of interest are noted below.

Ann-Marie Faria, Ph.D. She is the co-Project Director of this study and does not have any notable conflicts of interest.

Nicholas Sorensen, Ph.D. He is the co-Project Director of this study and does not have any notable conflicts of interest.

Jessica Heppen, Ph.D. She is the Principal Investigator of this study. Through her work with the National High School Center, Dr. Heppen was involved in designing the original versions of the Early Warning Intervention and Monitoring System, which was the basis of the interventions examined in this study. Dr. Heppen, who has designed and conducted a number of experimental evaluation studies, was also involved in the design of the current study and in contextualizing the findings in the broader literature. However, Dr. Heppen was not directly involved in any data collection or analysis.

Jill Bowdon, Ph.D. She is the lead analyst of this study and does not have any notable conflicts of interest.

Suzanne Taylor. She is an analyst on this study, and she does not have any notable conflicts of interest.

Ryan Eisner. He is an analyst on this study, and he does not have any notable conflicts of interest

Shandu Foster. He is a research associate on this study, and he does not have any notable conflicts of interest.

Notes

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1. The off-track flag definition is based on Allensworth and Easton's (2005, 2007) work on the on-track indicator.
2. National on-time graduation statistics are from 2013/14, with the exception of subgroup data, which are from 2011/12.
3. Early warning indicators and systems focus on on-time graduation, that is, graduating within four years of entering high school with a regular diploma, as the goal (Allensworth & Easton, 2007; Heppen & Therriault, 2008; Stetser & Stillwell, 2014).
4. "Data culture" refers to the ways in which schools use data to make decisions and identify students in need of additional support.
5. The final sample of 73 schools was larger than the intended sample of 72 because the marginal cost of including the last school was relatively low (see table B1 in appendix B).
6. Sensitivity analyses that used the continuous data instead of a binary flag for suspensions could not be conducted because some schools provided data on the number of days suspended, while others provided data on the number of suspensions; 22 schools did not clarify which type of data were provided.
7. An effect size is a standardized metric for reporting the magnitude of differences between two groups, expressed in terms of the number of standard deviations (for example, EWIMS schools were 0.27 standard deviations higher in school data culture than control schools). The What Works Clearinghouse (2014) considers effect sizes of 0.25 standard deviations or larger to be substantively important. That is, effect sizes of 0.25 or larger are interpreted as a meaningful effect, even though they may not reach

statistical significance in a given study. Hedges' *g* effect sizes use a pooled standard deviation across treatment and control schools.

8. The eight schools that stopped or never began implementing EWIMS in the 2014/15 school year were not considered to have formally dropped out of the study. Schools were only considered to have attrited from the study if they stopped participating in the student-level data collection or if their matched pair counterpart did not participate in the student-level data collection. Six of the eight schools that stopped or never began implementing EWIMS continued to participate in the data collection and were included in the study samples for the main impact analyses. See appendix D for a discussion of the reasons why these schools stopped implementing EWIMS.
9. Although the total number of EWIMS schools included in the impact analyses varied from 29 to 33 (depending on the outcome), the two schools that achieved moderate or high quality implementation were included in all analyses. The number of low-implementing EWIMS schools ranged from 27 to 31 (93–94 percent of the analytic samples for the different student outcomes in the impact analyses).
10. This may not indicate a problem with implementing EWIMS; rather, it may indicate that schools' own data systems provided all of the capabilities of the early warning data tool they were offered.
11. The number of students with uploaded data is larger than the size of the analytic sample for the EWIMS schools. This is because two EWIMS schools that did not provide outcome data for the study did upload student data into their tools during implementation.
12. There were 20 schools that received a score of 1 (27 percent), 11 schools that received a score of 2 (15 percent), 32 schools that received a score of 3 (44 percent), and 10 schools that received a score of 4 (14 percent).
13. Although eight EWIMS schools stopped or never began implementing EWIMS during the study, they were not considered to have formally withdrawn from the study if they continued to provide outcome data. Only two of the eight schools also formally withdrew from the study and did not provide outcome data; the remaining six were included in the analytic sample.
14. The study team also collected these data to inform intervention analyses at the end of the 2013/14 school year, before EWIMS implementation began.
15. In spring 2014, the survey response rate was 97 percent (71 schools).
16. Item difficulty reflects how positively an item is endorsed. Items with low item difficulty will be frequently and positively endorsed (for example, a high frequency of "Strongly Agree").
17. Students with exit codes of homeschooled were coded as having an unclear enrollment status because states and districts reported using this code for students who were under the state compulsory school attendance age (age 18 in all three states) but whose parents or guardians had formally withdrawn them from schooling.
18. In large sample sizes (those approaching infinity), Cohen's *d* and Hedges' *g* will produce the same standardized difference value. However, for smaller samples sizes, Hedges' *g* uses $N - 1$ in the variance estimate (as opposed to the N used in Cohen's *d* calculations, which underestimates the variance and therefore overestimates the standardized difference).
19. Interviews included exit interviews with schools that stopped or never began implementing EWIMS in the 2014/15 school year.
20. As mentioned, the 2014 surveys were only used to gather information on the interventions used in EWIMS schools.

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