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Delivery of State-provided Predictive Analytics to Schools: Wisconsin's DEWS and the Proposed EWIMS Dashboard

Bill Clune and Jared Knowles

Since 2012, the Wisconsin Department of Public Instruction (DPI) has maintained a statewide predictive analytics system providing schools with an early warning in middle grades of students at risk for not completing high school. DPI is considering extending and enhancing this system, known as the Dropout Early Warning System (DEWS). The proposed enhancements include better understanding how and why schools use a tool like DEWS, supports and training necessary to translate DEWS into school change, and extending DEWS into other domains such as college and career readiness.

This paper identifies national models of predictive analytic systems in education, including a focus on the Early Warning Implementation Monitoring System (EWIMS) (National High School Center, 2013). The paper explores how such policies might succeed in achieving their goals (e.g., dropout prevention and reduction of predictive at-risk behaviors), ways that districts and schools can make the policies more successful, and how states and state agencies like DPI might strengthen the policies, thereby facilitating local success. The paper recommends that DPI consider:

- fostering a network of schools for professional development and support of implementation of predictive analytics like DEWS and EWIMS;

- developing modifications of predictive analytic indicators to measure short-term change and progress;

- merging predictive analytics with findings of current research funded by the statewide longitudinal data system grant that will identify effective strategies for supporting students with different at-risk profiles;

- soliciting schools for voluntary implementation of the full DEW/EWIMS model; and

- sponsoring research on existing practices of how schools identify and intervene on behalf of at-risk students.

The analysis and recommendations of the paper should not be considered as final but rather as material for further discussion and deliberation—in essence as food for thought and inquiry.

The paper is organized as follows. First is a description of the details of DEWS as an example of implementation of a predictive analytics tool. Second is a logic model of the policy, which is the theory of change underlying its intended positive effects on outcomes. Third, beginning an initial assessment of the theory of change tracing the policy from schools and students, is an analysis of the strength of predictive analytic policies, using a framework developed by Porter, Floden, Freeman, Schmidt, & Schwille (1988). Fourth, following the logic model to the school level, is an analysis of the characteristics of organization and process required for successful implementation in schools, using a framework developed by Gamoran and colleagues (2003). Finally, the paper turns to the question of how outside agencies might enable successful implementation of predictive analytics, with a description of the results of a study of how three school districts supported use of college readiness indicators, followed by a discussion of how DPI might strengthen its own policies.

DEWS and the Proposed EWIMS Dashboard

For nearly 4 years, DEWS has provided all middle schools in Wisconsin with lists of their current students predicted to be most at risk for subsequent high school dropout (Knowles, 2015). Each student is assigned a probability of dropping out based on factors such as attendance, school discipline, mobility, and academic success in middle school. In addition to providing individual student predictions within the WISEdash Secure reporting tool for school districts, DPI provides a host of supporting documentation and user guides and encourages the development of in-person training through WISExplore—a data literacy training initiative.

DPI recently partnered with Regional Education Laboratory (REL) Midwest to study how DEWS is perceived and used by principals in middle schools across the state. A key theme from that report (unpublished) is that the link between DEWS and interventions is not as strong as it could be either conceptually or within the tool itself. There clearly is a need for DPI to provide additional guidance, tools, training, and a conceptual link between predictive analytics and student identification with existing or available student interventions and supports. This points to a key area of future work for DPI: connecting educator practice to predictive analytic tools. The leading national framework for this is the EWIMS model.

The central question for this paper is how predictive analytics like DEWS might be supplemented to strengthen implementation and outcomes at the school level where prediction, interventions, and outcomes actually occur. More generally, the question is how DPI as an agency not providing direct service to students might more strongly and constructively influence direct service through provision of data and analytics, a question that also applies to a college readiness early warning system, such as a College Readiness Early Warning System (CREWS), which is under consideration by DPI. This paper now turns to reviewing national work done to build such integrations, beginning with EWIMS.

EWIMS is an adaptation of research on data-driven decision making to the context of dropout prevention in middle schools, for example, the "plan, do, study, act" model for setting and achieving goals disseminated in Wisconsin as a school improvement process by WISExplore (Learning Point, 2004). An extension of DEWS to an EWIMS model would contain data on the risk factors identified by DEWS, as well as additional data from the school data systems called for by the EWIMS model. Schools would be able to add or subtract names of students from the at-risk list created based on their own criteria. DPI could create a dashboard pre-loaded with data from DEWS that includes fields in which schools can enter additional data such as grades, attendance, behavior indicators, and the interventions assigned to each student.

The intent of EWIMS in the middle grades is to identify at-risk students early and provide them with support so that they can get back on track for promotion to the next grade level and eventually graduate from high school. The guide and its tools for analyzing data are designed to help schools and districts:

- systematically identify students who show signs of struggling in school (an early indicator of risk) as identified by data such as DEWS and local criteria;
- match these students to appropriate interventions;
- monitor student progress in those interventions; and
- track the effectiveness of interventions over time.

Full implementation of EWIMS by schools involves seven steps:

1. *Establish roles and responsibilities*—create a team with a representation of key personnel; set meeting schedules, agendas, and goals; ensure that EWIMS is a top priority; provide the team with authority and resources;
2. *Establish and use the early warning system middle grades student tracking data tool*—set up the EWS data tool; load data;
3. *Review the early warning data*—review student data within and across middle school years; review patterns across students, time periods, and at-risk factors;
4. *Interpret the data*—analyze at-risk patterns; get new information from teachers, parents, and other school data;
5. *Assign and provide interventions*—build inventory of available interventions using the intervention mapping tool; assign students to interventions (e.g., according to a three-tiered model based on severity of need); identify gaps in interventions;
6. *Monitor students and interventions*—monitor student progress (e.g., attendance, review interventions for those still not on track); identify gaps in supports; study effectiveness of interventions in getting students back on track; recommend schoolwide strategies for common needs; share results with stakeholders;
7. *Evaluate and refine the EWIMS process*—analyze how to improve EWIMS process for next year; report on findings and recommendations; establish team for following year; validate local early warning indicators and thresholds for flagging students at risk.

Logic Model of the Intervention and Relationship to Research Questions

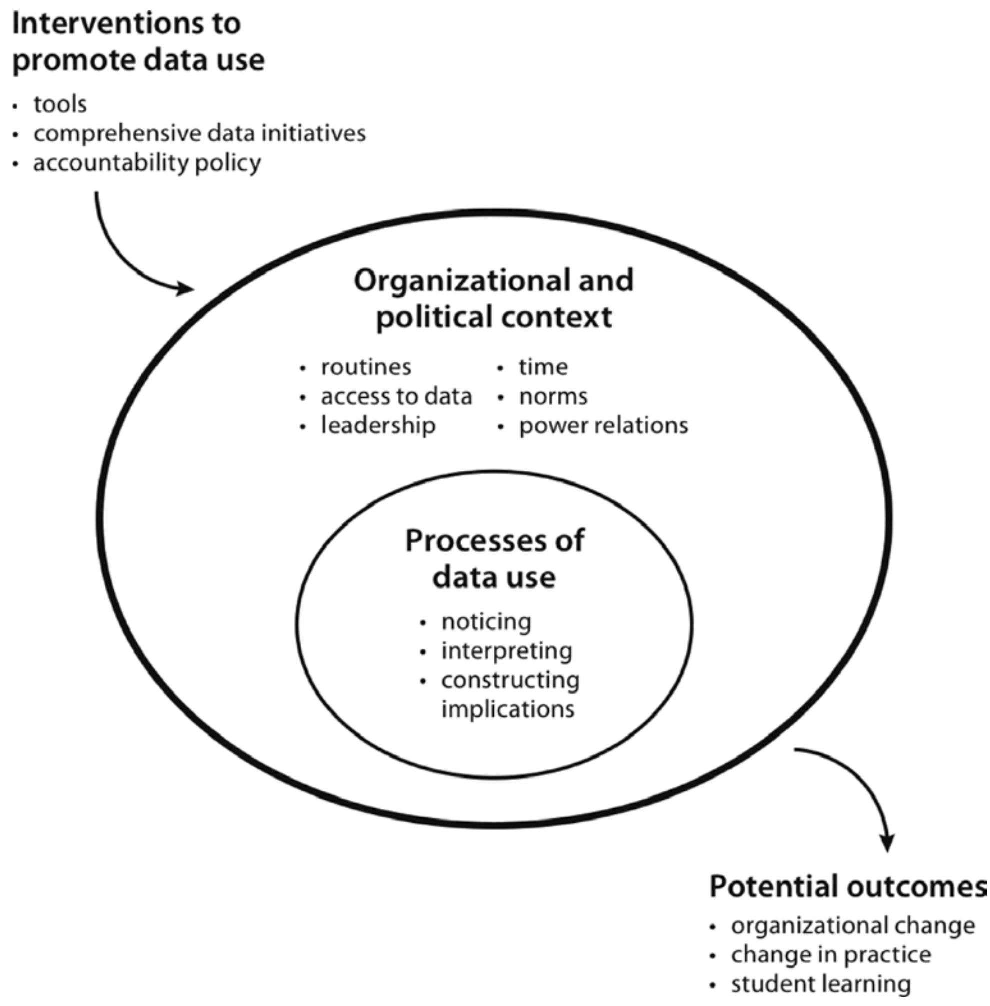
A logic model or theory of change is helpful for mapping the hypothesized causal mechanisms underlying why schools have adopted DEWS and could adopt the EWIMS model and how such interventions could be effective in changing student outcomes. A simple logic model is that:

1. DEWS data and EWIMS dashboard provided by DPI to all middle schools in Wisconsin
2. leads to analysis and reflection on the data in districts and schools
3. which leads to remedial actions on behalf of the students identified as at risk

4. which leads in middle schools to improvements for the identified students in the DEWS predictors (e.g., attendance, behavior, academic performance) and in high school to reduced drop out (again, presumably by the identified students).

According to Coburn and Turner (2011), who review and suggest a framework for research on data use, DEWS/EWIMS (and all such predictive analytics) probably would be considered a "tool" of data intervention (like a protocol), or data-driven decision making (Halverson, Grigg, Pritchett, & Thomas, 2007), intended to create the potential for different kinds of action, rather than a comprehensive initiative that includes multiple tools and professional development, or a data initiative tightly linked with accountability (Coburn & Turner, 2011, p. 186).

The Coburn and Turner (2011) article offers a logic model (which the authors call a framework) for "organizing research on data use" in schools that can be applied to DEWS/EWIMS (see figure).



Step 1 would consist of the intervention to promote data use, using such as tools and protocols as DEWS/EWIMS. Step 2 would include noticing and interpreting data and constructing implications for use, embedded in organizational processes supporting effective use of data, such as staff time, effective routines, school leadership, and culture. Step 3 would include (in addition to improvements in outcomes for individual students) improvements in supportive organizational processes—in other words, organizational change. The article reminds us that the final step in the logic model of delivery of predictive analytics "to" schools happens inside schools as delivery of services to students. The organizational factors needed to support the school process modeled by EWIMS will be discussed below in the section on school organization (analyzed in Gamoran et al., 2003).

The Strength of State-provided Predictive Analytics as a Policy Instrument

Predictive analytics like DEWS represent a class of state policies designed to influence local practice (that is, to be used and used effectively in schools). Helpful insights into the strengths and weaknesses of such policies can be gleaned from the five-part framework designed for analysis of policy strength by Porter and associates (Porter et al., 1988; see also Desimone, 2002; Polikoff, 2012). Their insights are helpful in understanding the aspects of the policies that may be expected to influence local practice intrinsically (of their own weight, through strong policy attributes) as opposed to areas of weak influence. Identifying areas of weak influence is useful for understanding where the policies inevitably depend more completely on local implementation (thus inevitably producing greater local variation) as well as where the policies might be supplemented through additional policy tools and resources.

The Porter framework predicts that the success of policies in influencing local implementation depends on the presence and strength of five policy attributes: specificity, consistency, stability, power, and authority. *Specificity* is the degree to which the policy provides clear, detailed, easily understood guidance about how the policy should be implemented, as well as its intent. *Consistency* is the extent to which parts of the policy and closely related policies are coherent with each other and send the same message to the implementer (inconsistent policies are fragmented and send conflicting messages). *Stability* is the presence of the policy over an extended time, which favors gradual learning about the policy and extended opportunities for local adaptation. *Power* consists of resources, rewards, and sanctions, such as funding, professional development, and accountability. *Authority* is the perceived legitimacy of the policy maker (the accepted right of the decision maker to issue such policies). Common sources of authority in schools are legal/ bureaucratic (based on law and legally defined roles) and expertise (based on expert knowledge). State policies do not usually rely on or possess traditional customary or charismatic authority.

Well-designed predictive analytics are typically strong on specificity, consistency, stability, and authority, and weaker on power. Specificity is a notable strength. DEWS/EWIMS, for example, provides middle schools with lists of students at risk of high school dropout, detailed information on each student's predictors, and supplementary guidance about remedial actions. The information is detailed and customized for each school, and the intent of policy is clear (dropout prevention). Consistency is strong in that the analytic package is delivered to every school, and state does not have other, inconsistent analytics. Authority is strong because DPI is the legally approved source of the policy, and local agencies are accustomed to DPI policy initiatives; in this case, though, the authority does not extend to mandated compliance. Stability is or can be one of the most important and least recognized strengths of predictive analytics. Stability exists if and to the extent that the authorities maintain the policy and policy tools over time and provide consistent guidance about implementation.

The limited power of predictive analytics policies like DEWS/EWIMS is due to their dependence on local schools for successful implementation. The main source of power is the policy tool itself as a resource available to schools at practically no cost. DEWS relieves schools of the administrative costs of identifying students at risk thereby freeing up resources for student assistance. Like other accurate predictive analytics, DEWS/EWIMS delivers a valuable technical resource otherwise unavailable to schools. The lists of students designated as at risk by DEWS, for example, do not always match the lists generated by schools from their own methodology and experience. Some students on the DEWS list are not identified as at risk by schools, and some students on local lists are not identified by DEWS (Knowles, 2015). Feedback from schools suggests that many are aware of the lack of overlap and attentive to the differences. For college readiness indicators like CREWS, the mismatch between predictive analytics and local experience may be even greater because of unreliability of impressionistic assessments.

The DEWS website offers a variety of supplemental resources, such as an Action Guide containing sections on combining DEWS and local data, guidance for action planning in use of DEWS by local schools, and a range of resources and references on dropout prevention strategies and research (with reference to state programs like Positive Behavioral Interventions and Supports [PBIS] and Response to Intervention [RTI] to deal with behavioral and academic difficulties). And DPI has conducted professional development sessions throughout the state on interpretation and use of DEWS data. Yet other sources of power are lacking, such as rewards, sanctions, and resources for high-quality implementation. Professional development may be provided by the state through vehicles such as WISExplore, depending on availability or resources and competing demands. A key question is how these resources might be leveraged to support organizational change. The policy often has just enough power to reach the threshold of the school (e.g., the desk of a school administrator), but implementation beyond that point depends on local willingness and capacity. The recent study by REL Midwest of DEWS (unpublished) suggests that this is indeed occurring in many schools with DEWS, but the fact remains that DPI cannot do much to motivate schools and districts to do anything with predictive analytical tools other than provide the data as a resource and offer strategically designed professional development. Other modifications of the system designed to increase its power are considered below in the section on options for DPI.

The next section considers the characteristics of school leadership and culture that would be required for successful deep implementation of a predictive analytic tool like DEWS/EWIMS. In other words, what would have to be systemically marshalled around local implementation?

Predictive Analytics, School Organization and Change

Although the DEWS/EWIMS dashboard provides a model for a process of school implementation, it does not explain what type of broader organizational structure and process in a school is necessary to support implementation. Professional development provided by DPI and other sources would need to promote these factors. The model of school organization and change relied on here was developed by Gamoran and colleagues (2003). The Gamoran framework concerns the type of school organization necessary to support teaching for understanding across a school. DEWS/EWIMS does not involve teaching for understanding, but the organizational requirements seem quite similar. Like teaching for understanding, early warning and intervention systems require new skills of monitoring and tracking individual students, responding to student needs, collaboration among team members, and orchestration of various types of school-level intervention and support. As with teaching for understanding, identification, support, and monitoring the progress of students from different grades and classrooms, assigned to different interventions, does not fit the traditional bureaucratic model of schooling where the goal is to buffer classroom teachers from outside interference. Instead, teachers and administrators must cooperate in a process that involves acquiring knowledge and skills outside the scope of normal teacher training and practice, such as interpreting the progress of individual students over time and evaluating the outcomes of remedial interventions. DEWS/EWIMS provides a model of a process that can be effective, but, following the Gamoran analysis, its performance in practice will be determined by the skills, communication, and trust across the team and its success in learning new skills over time.

The Gamoran analysis is essentially about the type of resources that must be provided to a development team in order for it to be successful as a professional learning community within the school and in collaboration with resources outside the school. Resources are classified generically as *material* (such as budgets and time), *human* (such as leadership and people with teaching and logistical expertise), and *social* (such as the norms of trust and collaboration present in professional learning communities and external networks). Such resources are necessary but not sufficient. What matters for effectiveness is how resources are translated and managed, how is time allocated, what tools and materials are available to teachers, how teachers' knowledge and skills are enhanced, and what activities lead to strong professional development among teachers. In other words, improvement consists of aligning resources with the task at hand. Resources also can be poorly aligned and mismanaged, thereby blocking success, for example, when leaders allocate resources to competing purposes. Conversely, greater alignment can magnify the effects of resources. In addition, professional development within the learning community can transform a small amount of resources into a larger amount, as when material resources provided to the team are transformed into additional human and social resources.

DEWS/EWIMS is itself a type of material resource, providing a model for the organization of a school-level early warning and intervention system and software for implementation. Yet, following Gamoran et al. (2003), teacher and staff time is the most critical resource for implementation. They must have convenient time set aside for collective planning and professional learning. Some of this time must be allocated for logistics, and some budget allocation also will be required. Any implementation of training around predictive analytics must be closely aligned and linked to existing efforts to avoid further encroaching on the limited time available for this work and duplicating efforts.

Leadership and expertise are the most important human resources. The essential tasks of leadership are constructing and selling the vision of the importance of an effective early warning system, building norms of trust and collaboration, supporting professional development, and monitoring implementation. The key goal is fostering the team as a professional learning community—in effect, as a circle of excellence. The team must be granted flexibility to learn and adapt and the authority to call on additional resources as required for new activities. All of this requires a balance between authority and expertise as sources of leadership. Traditional leadership from the school principal and administration is needed for management tasks like scheduling and budgeting. Growth of technical skills, like skillful implementation of DEWS/EWIMS (e.g., intervention, monitoring, evaluation, redesign), requires distributed leadership from experts within the DEWS/EWIMS professional learning community, the entire school, including the administration, and external social networks. Coordination of administrative and technical functions in a mutually reinforcing fashion is a task for distributed leadership across the school (and thus a key feature of organizational learning and change). A key task is integration of change with existing school-level systems of identification and intervention (e.g., PBIS). Note that change and effectiveness are long-term projects. Sustainability of leadership and resources over time is critical (and a challenge in the presence of rapid staff turnover). Sustainability of the policy at the state level must be matched with sustainable leadership in schools.

Use of College Readiness Indicators in Three School Districts

The previous section dealt with the organizational process needed for full effective use of predictive analytics like DEWS/EWIMS at the school level. This section summarizes a report on how three school districts implemented systems of early warning predictors and encouraged effective use in schools (Becker, Hall, Levinger, Sims, & Whittington, 2014). The district perspective is potentially instructive as a model because the goal of DPI, as with the districts, is to support effective implementation in schools from the outside, and many of the lessons learned from districts seem applicable at the state level.

Four takeaways of the report across districts are relevant to this paper and options for DPI (discussed further below):

1. Predictive analytics are not limited to predicting ultimate goals like high school graduation but may include measurements of change in at-risk factors during and across school years suitable for measuring progress and evaluation of interventions.

2. District leadership can create support, incentives, and accountability for implementation in schools, thereby increasing the probability of implementation and desired outcomes.

3. Concentrated focus of policy on improved performance around an especially important predictor (like 9th grade promotion) can serve as a catalyst and motivator for mobilization of effort and substantial short-term change in outcomes.

4. Prediction and intervention must be adapted to the local policy context in identifying at-risk students and available interventions.

The rest of this section will summarize findings from the three districts.

Prince George’s County Public Schools, Maryland (PGCPS)

Because analysis showed that approximately 20% of first-time 9th graders were retained each year and most failed to graduate from high school, district leadership opted for scoring a “quick win” with the new early warning system, using 9th grade promotion as the desired outcome.

Early warning indicator reports were created for incoming 7th and 8th graders, and each high school was charged with increasing its 9th grade retention rate by five percentage points from the previous year. Course grades from 8th grade were the best predictor of 9th grade promotion, followed by attendance, standardized test scores, and discipline, measured by number of suspensions. Updated early warning reports were provided to principals four times per year displaying the initial promotion probability from the beginning of the year, academic data from the previous year, new promotion probability, and new academic data, allowing staff to observe whether students were improving their likelihood of passing 9th grade each quarter. Because ninth graders were required to pass English 9, additional reports were created showing the English 9 grade distribution by high school and the number of students failing.

Supervisors monitored the principals throughout the year to observe the strategies that were used to support students identified as at-risk of repeating the 9th grade. School-based teams investigated causal factors by analyzing the cumulative files of each at-risk student and identified appropriate interventions for each. During the year principals were interviewed to learn what interventions they put in place. Focus groups were conducted with school staff and 9th grade students to collect information on the interventions and perceived effectiveness. English instructional specialists were sent to high schools that had struggled with 9th graders the previous year.

A clear sign of improvement was that the 9th grade promotion rate increased by 4.2 percentage points to 79.7%, closing the gap with the statewide average promotion rate of 86.8%. Summer school promotions may have increased the promotion rate by several more percentage points, exceeding the 5% goal.

Providence Public School District, Rhode Island

The Providence school district is governed by state proficiency-based graduation requirements covering six core academic areas deemed important for college and careers. Support for students was provided through individual learning plans in Grades 6–12 that monitored progress against the requirements. Student needs were identified through a data-informed decision making process. Interventions were selected from a list of evidence-based programmatic interventions that contained information on efficacy and target groups. Course performance and on-time progression through schooling were key indicators predicting graduation. Ninth grade promotion was also quite important. Students who reached 10th grade had a 73.3% graduation rate, those promoted to 11th grade 81%, but students who were retained at the end of 9th grade had a graduation rate of 15%.

The study recommended that updated measures of on-track status be used to measure improvement in at-risk factors and the success of programmatic interventions during the school year. Student status on the indicators would be updated throughout the 9th and 10th grades. Short-term indicators were recommended because they could serve as ongoing monitoring tools and provide opportunities for intervention prior to graduation even if they would not be as reliable as long-term outcomes like graduation. The district was exploring using the on-track indicator for internal school accountability.

Dallas Independent School District, Texas

The Dallas district developed indicators that were predictive of college readiness and success, defined as successful completion of a postsecondary credential. Research showed that more than 60% of graduates in the district begin their postsecondary careers in 2-year institutions and that among the students who enrolled in Dallas county community colleges, more than 60%

enrolled in at least one remedial/developmental course. Other research showed that a high percentage of students who took remedial courses eventually failed to complete a postsecondary credential. High school grades and attendance were consistently significant predictors of postsecondary enrollment. Two-year college enrollment was more difficult to predict, perhaps because the county community college district maintained an open-door enrollment policy to create greater access. Interestingly, the Dallas district's on-track variable was not predictive of enrollment, perhaps because 85% of the students analyzed (those who completed high school in 4 years) were on track for graduation at the end of 9th grade.

The district evaluation team produced monthly reports to high school counselors on applications for college admission and financial aid and evaluated the counselors, in part, on these measures. The district also introduced new activities that were designed to heighten student access to college, for example, paying for every 11th grade student to take the SAT on a school day and funding ACT testing for all students. Next steps included examination of remedial courses taken by the Dallas district's graduates who enroll in community colleges, and completing a data sharing agreement with the community college district.

Lessons Learned

First, predictive models are not limited to predicting ultimate goals like high school graduation but can include measurements of change in at-risk factors during and across school years. PGCPS created indicators allowing staff to observe whether students were improving their likelihood of passing 9th grade each quarter. Providence recommended the use of such indicators, and Dallas sent current data on applications for college and financial aid to high school counsellors.

Second, leadership can create support, incentives and accountability for implementation, thereby increasing the probability of implementation and desired outcomes. PGCPS was charged schools with increasing 9th grade promotion rate by 5% in 1 year, and the goal was probably achieved (see previous paragraph on gains in 9th grade promotion rate). Supervisors monitored the strategies principals used to achieve the goal. Dallas adopted college readiness as a priority goal and took steps to support students and supervise high school counselors on college applications, ACTs, and SATs.

Third, concentrated focus of policy on improved performance around an especially important predictor (like 9th grade promotion) can serve as a catalyst and motivator for mobilization of effort and substantial short-term change in outcomes. PGCPS focused on 9th grade promotion, creating indicators to monitor progress during the school year. This strategy of going for a "quick win" was likely instrumental in mobilizing multiple resources around what turned out to be an attainable goal. Providence also noted the importance of 9th grade promotion. Dallas evaluated high school counsellors on the basis of applications for college entrance and financial aid.

Fourth, prediction and intervention must be adapted to the local policy context in identifying at-risk students and available interventions. PGCPS first verified the critical importance of 9th grade promotion and shaped interventions around local requirements. Providence adapted indicators for use in individual education plans and structured policy responses around approved evidence-based interventions. Dallas understood the importance of gathering additional data to examine the role of remedial courses in the community colleges commonly attended by their students.

Options for DPI

As discussed, even in the absence of modifications, predictive analytics may be expected to have some influence as an authoritative expert resource that reduces local administrative costs and provides a different perspective on students at risk (e.g., correcting for under- and over-identification by teachers and schools). Because of these advantages, many schools already rely on these tools as an additional perspective in local policy.

This paper suggests additional options for DPI to deepen the utility and influence of these tools, as follows.

Create networks of experimenting districts and schools. Because DPI cannot mandate new local policies, options for extending the reach of predictive analytics would benefit from experimental implementation by a network of schools volunteering for experimental implementation of, for example, DEWS/EWIMS and CREWS. Research discussed in this paper, especially the Gamoran et al. (2003) study of school change, strongly suggests that school-level change depends on professional learning communities in schools and that expert networks are important resources for these communities. DPI has the capacity to sponsor such networks through its own resources and CSN/WISExplore.

Modify predictive analytics to measure short-term change. The research on college readiness indicators in school districts discussed above strongly suggests that adding measures of short-term change to predictive analytics (during and across school years) can increase their usefulness as tools for measurement of student progress and evaluation of interventions. Because progress of individual students is less intuitively obvious for teachers and schools than identification of which students are at risk, longitudinal measures may be more helpful and influential. Experimentation built around such indicators seems warranted, because the construction of longitudinal indicators involves novel technical issues and uncertainties about how the indicators would be used at the local level. Monitoring of student progress by schools is already an essential part of DEWS/EWIMS to be carried out qualitatively by school staff. This function could be strengthened and made more objective by creating predictive change indicators furnished by DPI.

Merge the proposed statewide longitudinal data system targeted intervention project with DEWS/EWIMS. Under its statewide longitudinal data system grant, as part of the emphasis on closing the achievement gap, and in conjunction with University of Wisconsin–Madison researchers, DPI proposes to identify strategies that fit customized profiles of individual students. This work could be merged with DEWS/EWIMS by modifying the dashboard to suggest intervention strategies customized to fit the circumstances of each identified student. This project is a natural application of predictive analytics and analogous to the individualized recommendations for future purchases generated through data mining by businesses like Netflix and Amazon.

Experimentally implement the full DEWS/EWIMS dashboard. Full implementation of the dashboard by interested schools is another interesting possibility. DEWS/EWIMS models a process and structure for end-to-end use of predictive analytics at the school level extending through prediction, warning, implementation, monitoring of progress, and system redesign. Schools willing to implement the model would be a rich source of information on the use and effectiveness of predictive analytics at the user level.

Collect and disseminate information on local practices of risk identification and intervention. DPI collection and dissemination of data on the use of predictive analytics statewide would be a useful service for districts and schools and a resource for networks. Because all schools have methods of identifying at-risk students, and because interventions like PBIS are common with significant variations likely across schools, implementation of innovations will require integration with dense existing systems of local practice. Data on the extent and shape of the local landscape should be quite useful for policy design. DEWS/EWIMS itself can be used to build a protocol for such research because it focuses attention on steps that would be required in any complete set of local practices (e.g., how at-risk students are identified, how interventions are selected, how students are assigned to interventions, how interventions are monitored, and the existing procedures by which to review and modify system performance).

Conclusion

This paper examined how DEWS and the proposed EWIMS dashboard, as examples of state-provided predictive analytics, are likely to be implemented, and how implementation and positive outcomes can be strengthened by DPI. Predictive analytics are valuable resources in themselves, but their use in schools can be enhanced through additional policy measures.

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