

# REPORT

FINAL REPORT

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## **A Conceptual Framework for Data-Driven Decision Making**

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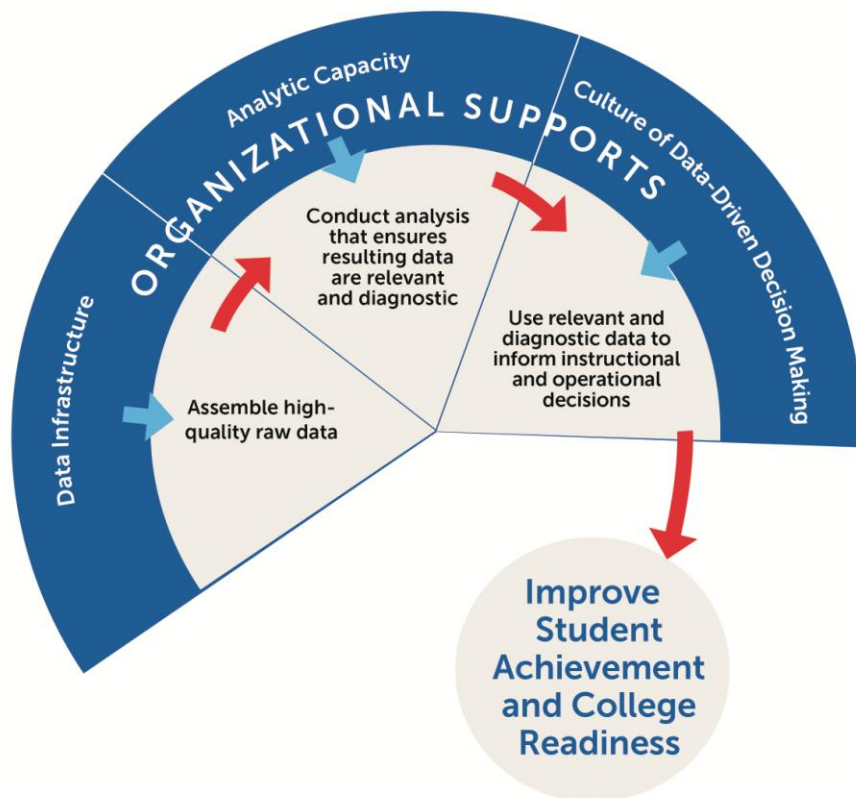
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As states, districts, and schools search for strategies to help raise student achievement and improve college readiness, they are using an increasingly wide range of data to inform decisions at all levels of the education system, from individual classrooms to the state department of education. Proponents of data-driven decision making have encouraged schools and districts to move toward a continuous quality improvement orientation, involving ongoing goal setting, measurement, and feedback processes that aim to (1) monitor and evaluate programs and processes and (2) link the results to individual and organizational outcomes (Datnow et al. 2007; Madinach 2012; Supovitz and Klein 2003; Wayman et al. 2007). Studies have established a relationship between levels of data use and increases in student achievement (Datnow et al. 2007; Slavin et al. 2013; Snipes et al. 2002). In the last decade, districts and schools have developed or implemented data systems capable of tracking the progress of individual students, teachers, and administrators from year to year or have formed data warehouses that allow them to combine data, such as teacher background and student test scores, across distinct databases and systems (Data Quality Campaign 2013; Paré and Elovitz 2005; Wayman et al. 2004).

In this data-rich environment, education decision makers have access to a wealth of information about students; teachers, administrators, and other staff; organizational finances and operations; and the communities that educational institutions serve. These data, however, have limited use—and could possibly be detrimental—if decision makers do not understand the benefits and limitations of data, the types of data relevant for the decisions they are confronted with, and how data can be appropriately used for decision making.

The Bill & Melinda Gates Foundation, which has funded four initiatives promoting strategic use of data at the state and district levels (see appendix), requested that Mathematica Policy Research develop a conceptual framework for data-driven decision making (DDDM) based upon knowledge generated from Mathematica’s evaluation of the strategic data use initiatives and from existing literature on data use in education. The framework, encompassed in this document as two key figures, aims to provide a comprehensive picture of the DDDM process in education. Separately, we also include an annotated bibliography of the literature we used to inform the framework.

The first of the two framework diagrams (Figure 1) provides a high-level, generalized view of a theory of action—a causal chain—for how DDDM can lead to improved student achievement and the supports and incentives needed to make effective data use possible. Figures 2a and 2b then map the process of DDDM at different levels of the education system, from classroom to state superintendent’s office, depicting the types of decisions that might be informed by data, the types of data needed to inform different decisions, and the importance of determining that the data are both relevant and diagnostic. We begin below by discussing the theory of action and its supports (Figure 1) before turning to the types of decisions, the types of data, and the identification of data as relevant and diagnostic.

**Figure 1. DDDM theory of action and organizational supports**

### A. The theory of action for data-driven decision making in education

Although data use activities take many forms, these activities must be grounded in a theory of action that explains how the data can be used to support the ultimate goal. In general, we assume that the ultimate goal is the improvement of student achievement and college readiness (though for some activities an immediate goal might be related to organizational supports, such as those discussed in Part B, below). At the broadest level, the general theory of action for DDDM involves three sequential steps that together could produce improved student outcomes; these are shown in the light wedges of Figure 1:

1. **Assemble high-quality raw data.** Depending on the decision at hand, data might be collected through formative, diagnostic, and summative assessments of students; standardized tests and college and career readiness exams; qualitative interviews, observations, or focus groups; surveys of staff, students, parents, and community members; financial, human resource, and administrative records; student records and transcripts; or labor, health, human service, education, and statistical agencies. We discuss the infrastructure supporting high-quality raw data in Part B, below.

2. **Conduct analysis that ensures resulting data are relevant and diagnostic.** If data are to serve decision making that ultimately improves student outcomes, they must be relevant to the decision maker and appropriately diagnostic for the decision at hand. We discuss these two characteristics in more detail in Part D, below, but the key points are these: Data that are not relevant to the decision maker (for instance, because they arrive too late to inform a decision) will not be used; data that are not diagnostic of the issue at hand (for instance, because they mismeasure the effectiveness of staff or programs or do not accurately assess student achievement) may be used in ways that are counterproductive.
3. **Use relevant and diagnostic data to inform instructional and operational decisions.** Even the best data and the best analysis will not improve outcomes if the results are not used. As we discuss in Part B, a culture of data use is necessary to ensure that (relevant, diagnostic) data are not filed away and forgotten.

## **B. Organizational supports for data-driven decision making in education**

The three steps of the theory of action outline the activities and hypothesized benefits of effective data use. The DDDM process may not occur, however, unless infrastructure, policies, and practices support it. As indicated in Figure 1, each of the three steps requires support.

**Assembling high-quality data requires strong *data infrastructure*.**

The creation and improvement of data systems are essential to an institution's ability to effectively collect, transfer, and manipulate information. Data infrastructure development includes the replacement or improvement of technical hardware such as servers, computers, peripheral devices, and Internet connections. *Establishing linkages* between distinct databases—for example, linking student and teacher data, linking financial data with program performance data—facilitates analyses that require connections across data types. *Creating low-burden data collection mechanisms*—for example, developing standardized procedures for the collection and storage of student achievement and behavioral data that are integrated with the existing work of teachers and other staff rather than imposing an additional burden—improves data quality and data security. Similarly, *certifying and monitoring those who collect data*, including school staff, support data quality. Adjusting data access and management practices to *ensure timely delivery* of data to decision makers enhances their ability to make use of the data. *Verification systems* are critical to ensuring the validity and integrity of data. For example, roster verification systems can ensure that teachers are correctly connected to the students they teach; enrollment audits can protect the integrity of data on attendance, truancy, and dropout.

**Producing relevant and diagnostic data analysis requires strong *analytic capacity*.**

Creating *in-house technical assistance systems* provides additional support to help decision makers (including teachers and principals) make use of data. These systems might include technical experts available to schools to support data system use or instructional coaches available to teachers to support the understanding and improvement of their professional

practice. This also includes requiring instructional coaches to explicitly incorporate data use into their teacher training and technical assistance activities. Establishing *external technical assistance contracts* for activities that are beyond an organization's internal capacity may improve the outputs of those activities. Depending upon an institution's capacity, this might include working with an external contractor to conduct value-added analyses or to improve a district's electronic data systems. Providing *training to staff at all levels* increases their individual capacity to access and use data. Important areas of training might include implementation of data driven decision making practices, how to access and analyze data, using data to change instructional practice, and data management and security. Improving the *accessibility of data* enhances the ability of educators at all levels to access and use data in a timely manner. This includes providing web access to diagnostic or benchmark assessments; ensuring that staff at all levels are presented with data in forms that are most likely to be relevant and diagnostic to their work; and instituting other methods of improving teacher, specialist, or administrator access to relevant information.

**Promoting effective use of relevant and diagnostic data to inform instructional and operational decisions requires a strong organizational culture of DDDM.**

At all levels of the education system, strong *leadership* and *systems of accountability* may facilitate successful data use. These include formal policies such as requiring and monitoring the use of specific DDDM practices, providing incentives for data use, or tracking teacher and administrator use of data systems. Similarly, leaders can increase the likelihood that data will be used by establishing a clear vision or strategic plan for DDDM. Promoting *data sharing* encourages staff to openly discuss and reflect on their data. This includes requiring or encouraging "data conferences" between staff and supervisors or a specialist as well as among peers. Allocating *time* and resources for data activities also encourages staff to examine and use their data. This is particularly important at the teacher and principal levels so that data analysis is not merely tacked on to the wide range of their existing responsibilities.

### **C. Decision makers and their data needs**

Meaningful use of data begins with *who* will access, analyze, or review the data and *for what purpose*. Here we describe the different users of data, by level, and the purposes for which they might conduct data analyses, which are presented in Figure 2a. Although Figure 2a is organized by the level of decision maker, it is important to recognize that data often flow across levels and that decisions based on data can affect multiple levels.

**Classroom teachers.** Either individually or in groups, classroom teachers primarily use data to *assess the needs, strengths, progress, and performance of their students*. This moves the teacher(s) to consider whether to *develop or revise current and planned classroom activities*. For example, a group of second grade teachers might examine their students' recent reading scores, then regroup students based on their progress. Teachers can also use data to *reflect on their own strengths and weaknesses*. For example, after her mentor records observations of a teacher's practice using a standard rubric, a teacher and the mentor discuss what the mentor observed, then determine that the teacher would benefit from attending an upcoming district-sponsored professional development session on classroom management.

**Figure 2a. Decision makers and data uses**

Educational DecisionMaker	Data Uses
Classroom teachers	<ul style="list-style-type: none"> <li>• Assessing the needs, strengths, progress, and performance of students</li> <li>• Developing and revising classroom instruction</li> <li>• Understanding professional strengths and weaknesses</li> </ul>
School administrators	<ul style="list-style-type: none"> <li>• Assessing the needs, strengths, progress, and performance of staff and students</li> <li>• Developing and revising school plans, targets, and goals</li> <li>• Monitoring the implementation of school practices, programs, and policies</li> </ul>
Superintendents, school boards, district staff, charter management organization leaders, charter authorizers	<ul style="list-style-type: none"> <li>• Assessing the needs, strengths, progress, and performance of schools, staff, and students</li> <li>• Developing and revising district curricula, standards, plans, targets, and goals</li> <li>• Monitoring the implementation and impact of district practices, programs, and policies</li> </ul>
State education agency officials	<ul style="list-style-type: none"> <li>• Monitoring statewide achievement and attainment levels, overall and for subgroups, statewide and by school/district</li> <li>• Monitoring and reporting measures of school performance (that is, value-added)</li> <li>• Measuring teacher value-added</li> <li>• Monitoring human capital pipeline</li> <li>• Evaluating program implementation and impacts</li> <li>• Developing and revising state standards, curricula, and goals</li> </ul>

**School administrators.** School administrators are charged with *assessing schoolwide performance*, which includes examining overall student performance *and* staff performance and progress. *Accomplishing the school's plans, targets, and goals* requires school administrators to *set and monitor school practices, programs, and policies* (often in collaboration with or with input from classroom teachers) that are intended to bring about change. To do this, they need data not only on raw student outcomes but also on the contributions of individual teachers to student achievement growth; on the classroom practices of teachers; and on their own performance (as rated by supervisors, teachers, or parents).

**Superintendents, school boards, district staff, charter management organization leaders, charter authorizers.** As with school leaders, the data use activities undertaken by district leaders (or leaders of other types of educational organizations, such as charter-school management organizations) often involve the *assessment of student learning and staff quality*. Using data to inform their efforts, district staff *adopt standards and develop—and, as needed, revise—curricula* when progress is lacking or has been exceeded. District leaders also *set and monitor districtwide practices, programs, and policies* and use data to examine whether the implementation and impact of these efforts has been maximized. Data to inform district-level decisions come from student assessments, classroom observations, school visits, staff surveys, revenues and expenditures, and other sources.

**State education agency officials.** A key job of state-level education agency officials is to perform analyses that *monitor statewide achievement and attainment levels*. Often, their work also involves reporting to federal agencies, districts, or other agencies. *Statewide student achievement must be monitored overall and for subgroups of students*, grade levels, districts, or schools. In addition, the quality of teachers and principals must also be ensured, so *teacher- and school-level value-added may be measured* to examine the current workforce, and teacher and principal certification programs may be monitored to ensure the quality of the future education workforce. Finally, state education agency officials are responsible for *measuring and evaluating the implementation of programs and activities* that are in pilot phases across some districts or schools or have been fully rolled out in the state.

## **D. Identifying relevant and diagnostic data**

As indicated in the theory of action (see Figure 1), in order to guide the improvement of practice—and ultimately the improvement of student outcomes—data must be *relevant* to the practice of the particular decision maker and *diagnostic* for the issue at hand. Irrelevant data will not be used, and nondiagnostic data might be used inappropriately. If the data provided are not relevant and diagnostic, educators are more likely to end up drowning in data than driven (in the right direction) by data. Here we discuss Figure 2b, which presents factors that might be considered in assessing the likely relevance of the data and the distinctions between diagnostic and nondiagnostic data.

### **1. Are the data *relevant* to the decision maker and the decision at hand?**

As indicated in Figure 2b, different kinds of data are relevant for decision makers at different levels of the education system. For each level of decision maker, the relevance of data may depend on whether they are related to students, staff, or programs; how frequently the data are updated and delivered; and the level of detail or aggregation. Teachers, for example, typically need student data that are fine-grained—at the level of individual students and specific skills—and rapidly delivered if they are to use the data to adjust their instruction. Data on annual end-of-year state assessments are of limited use to teachers for informing daily instruction because the results typically come back after the school year is over and after students have moved on to the next grade. Relevant data for teachers, for example, might be in the use of technology that allows a teacher to query students and have students submit their responses for an immediate check for understanding.

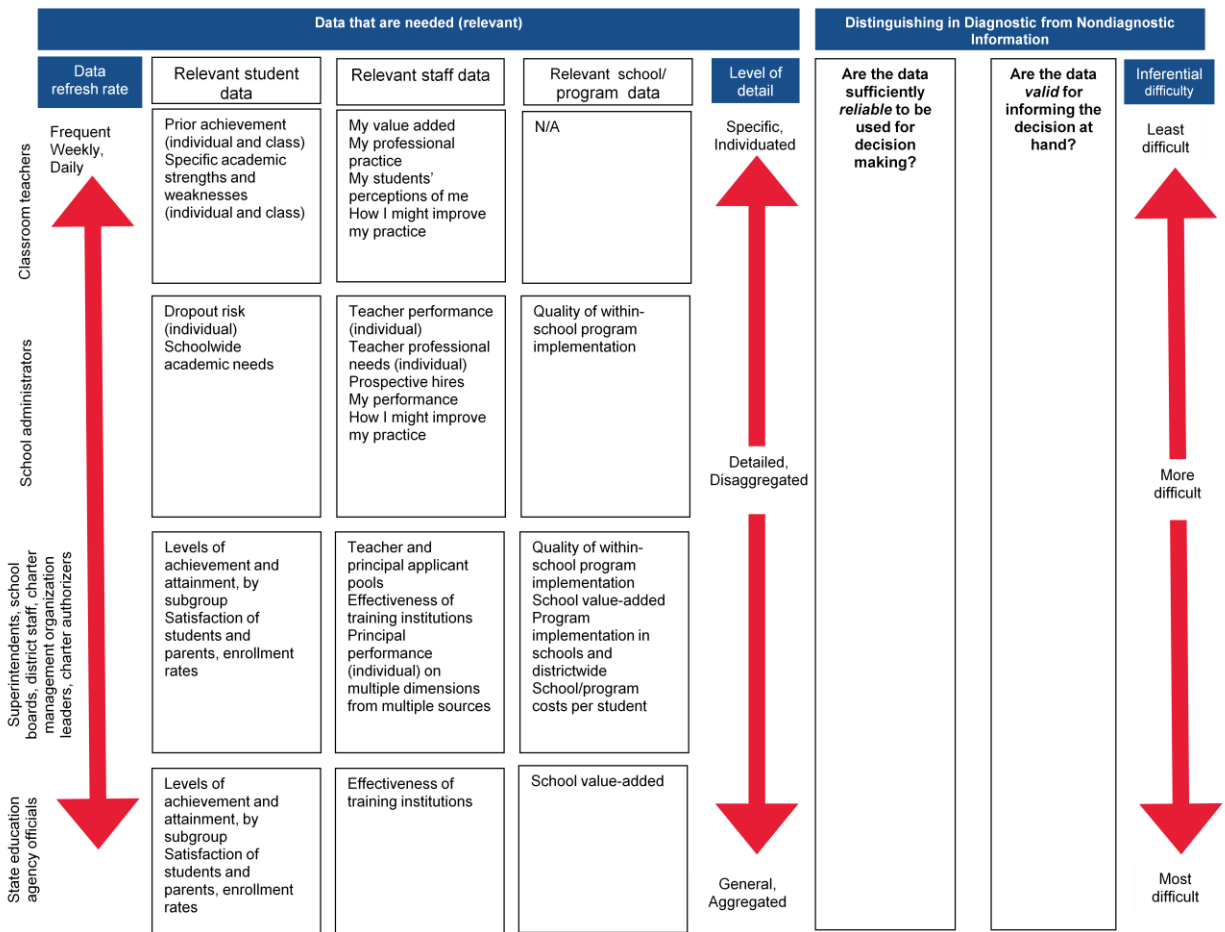
Decision makers at higher levels of the system typically need data that are aggregated at larger units of analysis (teachers rather than students, schools rather than teachers, and so on), and their decisions often do not require data that are updated as rapidly and frequently. For example, decisions about human capital or accountability regimes are not made on a daily basis and therefore do not require data that are updated daily. Higher-level decision makers are likely to need a wider range of types of data on programs and staff as well as on students.

### **2. Are the data *diagnostic* for informing improved decisions?**

The relevance of the data to the decision maker and the decision at hand is not sufficient to ensure that the data will move the decision maker in a productive direction. Student achievement data, for example, are certainly relevant to assessing the performance of the school, but if not



**Figure 2b. Relevant and diagnostic data**



analyzed carefully, they could lead to bad inferences about the school’s performance and bad decisions about how to improve the school’s performance. The same data can be diagnostic for some decisions and not for others. A teacher’s value-added, for example, might be diagnostic for informing a principal’s hiring decision, but it is not, in itself, diagnostic for how to improve the teacher’s practice because it provides no information about what the teacher is doing to achieve his/her value-added. In order to be diagnostic, the data must be *reliable* and *valid* for informing the decision at hand, as we explain below.

*Reliable* data are measures that do not have large random variation when they are measured repeatedly. Unreliable data lack stability: they involve so much random variation (or statistical “noise”) that they are essentially uninterpretable. The human brain has a tendency to find patterns in data even if there are no real patterns—to be “fooled by randomness” (Taleb 2001). In the education context, single-year measures of teachers’ value-added have sometimes been criticized as insufficiently reliable because they can change substantially from one year to the next even if the teacher’s true performance has not changed; the best methods to determine value-added improve the reliability of their results by averaging across multiple years of teaching and by making statistical adjustments to account for reliability.

More generally, reliability tends to be a bigger challenge for measures that focus on changes or differences in other underlying measures (for instance, achievement gains versus achievement levels). Subtracting one result from another makes the random variation in each of the two measures a larger proportion of what is left. For example, even if a student assessment produces a reliable measure of a student's current achievement level, a measure of the change in the student's achievement from one test to the next may be unreliable. This can be especially challenging for teacher-developed assessments such as those that are sometimes used for "student learning objectives." Teachers should be very cautious of overinterpreting the apparent change in achievement from one test to the next for any individual student. In general, educators and policymakers should try to understand the reliability of data before using them to make decisions, especially if those decisions involve high stakes.

Even when data are reliable, they may not be *valid* for informing the decision at hand. Data that are improperly analyzed or interpreted can lead to invalid inferences that are biased, that is, that cause decision makers to draw exactly the wrong conclusions. Using student achievement data to assess the effectiveness of teachers, principals, schools, or interventions is especially susceptible to biased (invalid) inference because student achievement can be affected by many factors that are unrelated to the effectiveness of staff, schools, or programs. For example, judging a teacher's effectiveness based on the achievement of her students without accounting for the prior achievement of those students would lead to many exemplary teachers being labeled as ineffective simply because they serve disadvantaged students. This is not to say that student outcomes data should not be used to evaluate effectiveness, but care in the analysis of such data is critical for avoiding faulty inferences. In many cases—notably the measurement of teacher and school value-added—the analysis needed to produce valid inferences is complicated, and a district or state may want to consult outside experts to conduct it.

As Figure 2b suggests, the difficulty of analyzing data to draw valid inferences for decisions tends to increase with the decision maker's level in the structure. Teachers need to know, for example, the academic strengths and weaknesses of their students, which typically can be directly identified using assessments. Principals need to know what individual teachers are contributing to student achievement growth—a more difficult concept to measure. Raw student achievement data may be valid for purposes of understanding the skills of individual students but invalid for understanding teachers' contributions. District officials need to be able to assess the effectiveness of each principal, which is even more difficult than assessing the effectiveness of a teacher because principals' effects on student achievement may take considerable time to become apparent and because principals' professional practice is difficult to observe. Similarly, state officials need to know whether the takeover of a school or district is called for and what kinds of interventions are most likely to improve the performance of the school or district—decisions that ideally require data on the effectiveness of alternative interventions, the capacity of local staff, the pool of human capital from which to draw, and various aspects of the local context.

In sum, being driven by data requires much more than the *existence* of an effective data infrastructure, the accessibility of the data, and a culture of data use. It also requires careful attention to ensuring that data are *both* relevant and diagnostic for each decision maker and decision. Otherwise, there is a high risk that decision maker will either drive in the wrong direction or drown in the data.

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## **APPENDIX A**

### **BACKGROUND ON THE STRATEGIC DATA USE INITIATIVES**

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As districts and schools continue to search for strategies to help raise student achievement and improve college readiness, the use of data to inform decision making and strategic planning represents a promising strategy. As part of its effort to help educators use data to improve teachers' effectiveness and increase students' college readiness, the Bill & Melinda Gates Foundation contracted with Mathematica Policy Research to conduct an evaluation of progress from its investments in four initiatives. The evaluation is examining how grantees have implemented the initiatives, identifying key challenges and promising strategies, and gauging impact. The evaluation focuses on six core research questions:

1. What factors affect agencies' capacity to analyze data well?
2. How are data analyzed, particularly as they relate to teacher effectiveness and college readiness?
3. How are data and analytic results disseminated to key stakeholders?
4. What challenges did agencies encounter in enhancing organizational capacity to generate and use data, and what are promising strategies for meeting these challenges?
5. How are decisions related to teacher effectiveness and college readiness better informed by data in the wake of the strategic data use initiatives?
6. What challenges did agencies encounter in making decisions related to teacher effectiveness and college readiness, and what are promising strategies for meeting these challenges?

The four strategic data use initiatives focused on supporting the strategic use of education data at the state and district levels. They are described below.

The **Strategic Data Project (SDP)** partners with state education agencies, school districts, and charter school networks to transform the use of data in education to improve student achievement. The program places and supports skilled staff in partner agencies for two-year fellowships.

**Education Pioneers (EP)** mobilizes and prepares a national network of talented leaders, managers, and analysts to transform education into the best led and managed sector in the United States. The program places early- or mid-career professionals from multidisciplinary backgrounds in leadership, management, and analytic roles in education agencies for 10-month fellowships.

The **National Student Clearinghouse (NSC) pilot** sought to develop high quality, actionable reports linking K-12 and postsecondary data that can be used by schools, districts, and states to improve the college readiness of their students.

The **Teacher Student Data Link (TSDL) project** aims to improve the validity and reliability of K-12 teacher-student data links, to enable states and districts to better measure teachers' contributions to the achievement growth of their students.

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