NOVEMBER 2015

Continued Progress

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Promising Evidence on Personalized Learning

RAND CORPORATION

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To download the *Survey Results Addendum,* visit www.rand.org/t/RR1365.

RR-1365-BMGF
November 2015

This report is based on research funded in part by the Bill & Melinda Gates Foundation. The findings and conclusions contained within are those of the authors and do not necessarily reflect positions or policies of the Bill & Melinda Gates Foundation.

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Introduction

The Bill & Melinda Gates Foundation has engaged RAND to carry out an ongoing study of foundation-funded schools that are employing promising approaches to personalized learning. This research is part of a public commitment the foundation has made to spread effective practices across districts and charter networks, develop innovative roles for teachers, and support implementation of college-ready standards. This is the second report in a series focused on the achievement data, school design characteristics, and teacher and student perceptions of schools implementing personalized learning.

The achievement findings in this report focus on 62 public charter and district schools that are pursuing a variety of personalized learning practices. All of the schools received funding from the Gates Foundation, either directly or through intermediary organizations, to implement personalized learning practices as part of at least one of the following three foundation-supported initiatives: Next Generation Learning Challenges (NGLC), Charter School Growth Fund's Next Generation School Investments, and the Gates Foundation's Personalized Learning Pilots. (See page 36 for more detailed descriptions of these initiatives.) Each of the schools was selected to participate in these initiatives through a competitive process, which included a rigorous evaluation of its leadership team and its instructional vision.

The implementation findings focus on 32 NGLC schools that implemented personalized learning models and administered the Northwest Evaluation Association (NWEA) Measures of Academic Progress (MAP) mathematics and reading assessments during the 2014–15 school year.[1] The schools are located predominantly in urban areas with the exception of two rural schools. They tend to serve large numbers of minority students from low-income families. According to information provided by administrators, the school-level median of students of color is 75 percent, and the school-level median of students eligible for free or reduced-price lunch is 80 percent.

The concept of personalized learning has been around for some time, but the adoption of personalized learning approaches has increased significantly in recent years due in part to rapid advances in technology platforms and digital content. Although there is not yet one shared definition of personalized learning, leading practitioners in the field generally look for the following: (1) systems and approaches that accelerate and deepen student learning by tailoring instruction to each student's individual needs, skills, and interests; (2) a variety of rich learning experiences that

1 Although assessment data were available in a large number of schools that use the assessment, data collection related to implementation was limited to schools funded through the NGLC program.

collectively prepare students for success in the college and career of their choice; and (3) teachers' integral role in student learning: designing and managing the learning environment, leading instruction, and providing students with expert guidance and support to help them take increasing ownership of their learning.

Although these core attributes are common among the schools in the study, there is considerable diversity in the details of the schools' instructional models because innovation was encouraged in the competitive grant programs they participated in. That is, the schools in this study are not adopting a single standardized model of personalized learning. Despite the wide variety of personalized learning models in these schools, the Gates Foundation, along with other funders and leaders in the personalized learning space, identified five strategies that are often present in the schools. As the following descriptions suggest, each strategy encompasses a set of tools and features of the personalized learning environment. Some of these, such as the provision of flexible pathways, are central to a personalized approach, whereas others (e.g., use of technology) might be viewed more as enablers of personalized learning. This framework provides a useful way to organize discussion of school design features and implementation.

LEARNER PROFILES: This strategy seeks to give teachers an up-to-date record that provides a deep understanding of each student's individual strengths, needs, motivations, progress, and goals to help inform his or her learning. Teachers work with students to create individual goals; student data are provided to students, and teachers discuss these data, along with the students' goals, with the students; and data from multiple sources (e.g., projects, tests, quizzes, presentations, software, or non-cognitive factors) are used to understand student progress.

PERSONAL LEARNING PATHS: This strategy holds all students to high expectations, but the school model allows for flexibility in the path that students take through the content. Students are able to make choices about the content or structure of learning and the school uses a variety of instructional approaches and curriculum materials to meet the learning needs of all students. In addition, there is time during the school day for one-on-one academic supports for students that are tailored to their learning needs, whether these needs focus on remediation, help with grade-level content, or enrichment. Finally, there are opportunities for students to engage in meaningful learning experiences outside of school.

COMPETENCY-BASED PROGRESSION: In this strategy, each student's progress toward clearly defined goals is continually assessed, and assessment occurs "on demand" when a student is ready to demonstrate competency. Assessment may take a variety of forms, such as projects or presentations, as well as more traditional tests and quizzes. A student advances and earns course credit (if applicable) as soon as he or she demonstrates an adequate level of competency. Students advance through the content at their own pace.

> *The adoption of personalized learning approaches has increased significantly in recent years due in part to rapid advances in technology platforms and digital content.*

FLEXIBLE LEARNING ENVIRONMENTS: This strategy means that the school uses resources such as staff, space, and time in flexible ways to support personalization. For example, elements of the learning space—size, classroom organization, and furniture—enable, or do not hinder, implementation of personalized learning. The structure of learning time and student grouping strategies are flexible, responsive to student needs, and, in the case of grouping strategies, based on data. Technology is a key aspect of the school model and is available to all students, and often schools provide a device to each student.

EMPHASIS ON COLLEGE AND CAREER READINESS: The school's curriculum, activities, and programs are intended to develop college and career readiness, in terms of academic and non-academic skills. Some examples are college visits, career surveys, career-oriented internships, college-level courses, or encouragement of college expectations. Aspects of curriculum, activities, or programs (including student advisory strategies) are intended to develop students' skills and competencies beyond academic content (referred to variously as "habits of mind," "learner identity," "student agency," "non-cognitive skills," etc.). This strategy also involves developing students' college and career preparation skills.

Research Design

Data Sources

We obtained and analyzed both qualitative and quantitative data from each school to create a broad picture of the schools' efforts to implement personalized learning and to understand the outcomes that resulted from the adoption of these new teaching and learning practices. We collected information using the following methods; additional details are available in the Appendices.

RAND collected the following information to conduct its analyses:

- Site visits
- Interviews with school administrators
- Teacher logs
- Teacher surveys
- Student surveys
- National surveys
- Achievement data for personalized learning students
- Achievement data for a matched comparison group of students

SITE VISITS: We conducted one-day site visits at seven schools in spring 2015. The visits included a one-hour interview with the principal, 45-minute individual interviews with three instructional staff, a one-hour focus group with six to eight instructional staff, a one-hour focus group with six to eight students, and 10- to 15-minute observations of at least two classrooms, one mathematics and one English language arts (ELA). The purpose of the site visits was to gather in-depth information about implementation of the school model and instructional practices and to solicit student perspectives.

INTERVIEWS WITH SCHOOL ADMINISTRATORS: We interviewed an administrator by telephone at each school, district, or charter management organization in the fall of the 2014–15 school year. We conducted a second set of telephone interviews in the spring with an administrator at the school level, usually the principal or assistant principal. At site visit schools, the spring administrator interviews were conducted in person. The interviews helped gather other information about instructional practices, including what types of technology the school was implementing, whether the school used standards-based grading, and whether there were opportunities for learning outside of school. The interviews lasted one hour.

TEACHER LOGS: Teachers of mathematics and ELA were asked to complete logs, which were brief, online surveys that included questions about daily instructional practice and the factors that influenced their teaching on a particular day. We administered the logs over two 10-day periods in 2014–15, once in the fall and once in the spring, for a total of 20 logs per teacher. In the fall, 181 teachers completed at least one log, for a response rate of 70 percent. In the spring, 153 teachers completed at least one log, for a response rate of 59 percent.

TEACHER SURVEYS: Teachers of mathematics and ELA were also asked to provide their perceptions about various aspects of the models, including professional training and support, access to resources, the quality of instructional and curricular materials, use of different models of classroom instruction, use of technology in the classroom, use of data to assess student progress, and obstacles to implementation. The survey was distributed to a sample of 261 teachers and the response rate was 74 percent. The teacher surveys were administered online in spring 2015.

STUDENT SURVEYS: Students were asked to describe their study habits, attitudes toward learning, perceptions about their school, the level of access to technology, and other topics. The student surveys were administered online in the fall and spring of the 2014–15 school year to students in 29 schools with enrolled students who met the age criteria: grades 6 and above or age 11 and older if the school did not use traditional grade levels. The fall survey focused on study habits and attitudes toward learning; the spring survey supplemented these with the remaining topics. Student responses to items that appeared on both surveys were similar, so this report focuses on the spring results that cover the broader range of topics. We distributed the fall survey to 7,214 students and the spring survey to 7,023 students. Response rates were 74 percent and 77 percent, respectively.

NATIONAL SURVEYS: To provide comparative data for our teacher and student surveys, the Gates Foundation engaged Grunwald Associates to administer the surveys to a national sample. Those surveys were administered during the summer after the 2014–15 school year. The questions on the survey were nearly identical to those on our surveys, although the language was adapted to refer in the past tense to the 2014–15 school year.

ACHIEVEMENT DATA FOR PERSONALIZED LEARNING STUDENTS: The study relies on data from the NWEA MAP assessment. In schools that use MAP, students generally took the mathematics and reading assessments online at least twice per school year, in the fall and spring. The MAP assessment produces scores on a continuous scale that can provide information about how much progress a student makes over the course of a school year or longer periods.

ACHIEVEMENT DATA FOR A MATCHED COMPARISON GROUP OF STUDENTS: This study uses a matched comparison group design. NWEA, through its standard service known as "virtual comparison group" (VCG), drew on its large national database of testing data to identify students who had starting performance similar to the personalized learning students and who were attending schools serving similar populations. Details about the matching method are described in Appendix section A1.2. This process enabled us to make "apples to apples" comparisons of learning growth between the students at the personalized learning schools and a similar population of students attending other schools.

Methods and Limitations

Despite the increased interest in personalized learning, the field lacks evidence about its effectiveness. This study is designed to address this need using the most rigorous method that can be applied to the foundation-funded set of schools. In particular, given the implementation design for the portfolio of personalized learning schools in the study, it was not possible to create randomly assigned treatment and control groups; nor did we have access to data from neighboring schools that might have matched the personalized learning schools. As new schools, they lack a history of data from before they began implementing personalized learning, which would have enabled other analytic methods for determining achievement effects. With these limitations, the VCG approach, as a matched comparison group design, is the best available quasi-experimental method for estimating personalized learning treatment effects. If the personalized learning group and the VCG are equivalent at baseline, this method can produce unbiased estimates.

We report achievement effects of personalized learning using effect sizes, a standard way researchers measure the impact of an educational strategy. This allows researchers to make comparisons across research studies. To assist with interpretation, we also translate the effect sizes into the percentile rank of a personalized learning student who would have performed at the median (50th percentile) if he or she had been in a non-personalized-learning school.

We find that the observable characteristics of the comparison students are well matched to those of personalized learning students in the study. However, the comparison students could possess other unidentified or unobserved differences from the personalized learning students that could confound efforts to measure the impact of the personalized learning environment. For example, parents of personalized learning students might have greater interest in non-traditional schooling environments and this could be related to how well their children do, independently of the personalized learning treatment. Differences such as this are a type of selection that could bias our estimates of personalized learning treatment effects in either direction. The VCG approach also assumes that the students in the comparison group are attending more traditional schools that are not using personalized learning practices, but there is no way to verify this assumption. If this assumption is not true—if any of the comparison schools were indeed using personalized learning practices—estimates comparing personalized learning students to VCG students could be biased toward zero.

When interpreting the implementation data, it is important to keep in mind the limitations of the data sources, which rely on the self-reports of stakeholders who voluntarily participated. We have no independent means of verifying the accuracy of their responses. Where response rates are lower, particularly for the teacher survey and logs in some schools, responses may not accurately represent the perceptions of the whole stakeholder group, limiting generalizability. Survey responses are likely to vary across several factors, such as grade-level configuration (e.g., elementary versus secondary schools) or by type of school (e.g., charter management organization, independent charter, or district-sponsored school), but we avoid breaking down the data by these features because of the small numbers of respondents in some categories. Although we weighted the national student and teacher surveys to make the respondent profiles more similar to the personalized learning samples, data limitations prevented us from doing so with respect to family income, limiting the comparability of the student survey samples.

Additional details of methods used in the data collection and analyses, and corresponding limitations, are described in Appendix 1.

Summary of Findings

The findings are grouped into four sections. The first section on student achievement finds that there were positive effects on student mathematics and reading performance and that the lowest-performing students made substantial gains relative to their peers. The second section on implementation and the perceptions of stakeholders finds that adoption of personalized learning practices varied considerably. Personalized learning practices that are direct extensions of current practice were more common, but implementation of some of the more challenging personalized learning strategies was less common. The third section relates implementation features to outcomes and identifies three elements of personalized learning that were being implemented in tandem in the schools with the largest achievement effects. Finally, the fourth section compares teachers' and students' survey responses to a national sample and finds some differences, such as teachers' greater use of practices that support competency-based learning and greater use of technology for personalization in the schools in this study with implementation data.

The findings are grouped into four categories:

1 Student Achievement Results

2 Implementation Findings

3 Relating Implementation to Outcomes

4 National Comparison of Survey Results

Student Achievement Results

Key Findings

- A majority of schools had positive effects on student mathematics and reading performance over two years, echoing results from last year but with a sample nearly three times as large.
- Growth continued to accumulate in a third year in schools that started implementing personalized learning by 2012.
- Scores grew substantially relative to national averages.
- A large proportion of students with lower starting achievement levels experienced greater growth rates than peers, particularly in mathematics.
- Results were widespread, with a majority of schools having statistically positive results.
- District schools in the aggregate did not show significant positive effects, but the sample size was small.
- The findings withstand a series of rigorous sensitivity analyses.

Overall, these findings suggest that the effects of personalized learning on student achievement are promising.

For the 62 schools for which two years' worth of student achievement data were available, this study found that students attending these schools made gains in mathematics and reading over the past two years that were significantly greater than a comparison group made up of similar students selected from comparable schools.

Achievement analyses find that there were positive effects on student mathematics and reading performance and that the lowest-performing students made substantial gains relative to their peers.

These gains in both mathematics and reading translate into effect sizes that are relatively large compared with those measured in studies of other types of interventions. Although results varied considerably from school to school, a majority of the schools had statistically significant positive results. Moreover, after two years in a personalized learning school, students had average mathematics and reading test scores above or near national averages, after having started below national averages.

The study analyzed mathematics and reading scores for approximately 11,000 students who were enrolled in the 62 schools during the 2013–14 and 2014–15 school years. There are 62 schools included in the achievement analysis for mathematics and 61 included in achievement analysis for reading. All of these schools implemented personalized learning schoolwide during at least the two academic years of

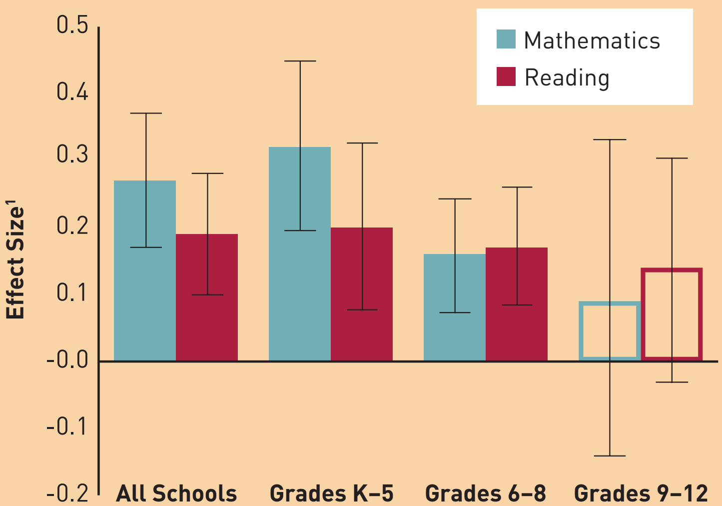
2013–14 and 2014–15. They all also administered the NWEA MAP both years. MAP is an online adaptive test in which the test software adjusts the consecutive difficulty of questions in response to an individual student's answer. If a student responds incorrectly, the next question is easier; if a student responds correctly, the test software progresses to a more complex question. The MAP assessment can provide accurate information over a broad range of primary and secondary student ability, including how much progress a student makes over the course of one or more school years. Where noted, the achievement analysis also includes a subset of 21 schools that also met the inclusion criteria for the 2012–13 school year, thus enabling an examination of achievement over a longer period of time.

The two-year effect sizes for this student population across all schools were 0.27 in mathematics and 0.19 in reading. There were positive results across all grade levels, although the effects tended to be larger in the elementary grades and were not statistically significant in the high school grades. These results are shown in Chart 1.

CHART 1

Students made significant gains in mathematics and reading, overall and in elementary and middle schools

Fall 2013 to Spring 2015



	All Schools		Grades K–5		Grades 6–8		Grades 9–12	
Percentile Gain[2]	11	8	13	8	6	7	4	5
Number of Students	11,217	10,906	7,742	7,577	2,593	2,391	882	938

[1] *Solid bars indicate statistical significance (p < 0.05) after adjustment for multiple hypothesis tests. Outlined bars are not significant.*

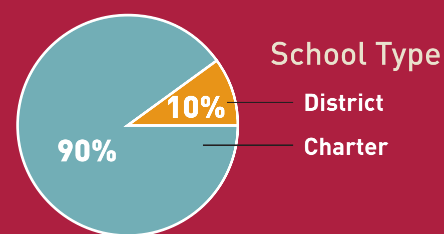
[2] *Percentile gains translate the treatment effect sizes into the amount of improvement experienced by the median student.*

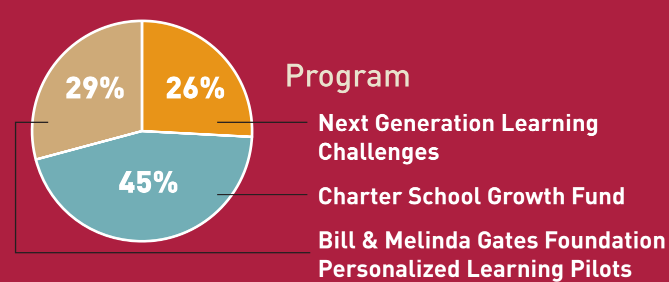
Composition of schools in student achievement results

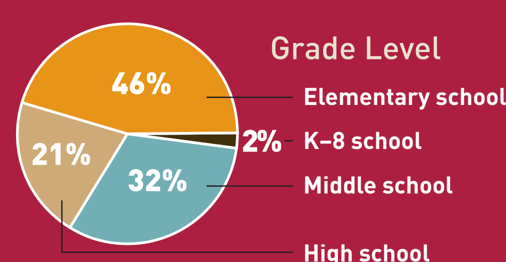
Schools Implementing Personalized Learning in Fall 2013 or Earlier

About **11,000** students

62 schools







To translate the effect sizes into more readily interpretable numbers, Chart 1 also presents the effects in terms of percentile point gains. The 11 percentile point gain for mathematics across all schools means that a student who would have performed at the median (50th percentile) in a non-personalized-learning school is estimated to have performed at the 61st percentile after two years in a personalized learning school.

Growth continued to accumulate in the third year in schools that started implementing personalized learning by 2012.

Chart 2 presents the overall results for the 21 schools that started implementing personalized learning in 2012 or earlier and continued to use the MAP assessment in 2014–15. In this group of schools, we find large and significant positive results for personalized learning, with the treatment effect accumulating over time (although the effect is not purely additive—for example, the two-year effects were not as large as double the one-year effects). Chart 3 shows that this group of schools exhibited larger effects from 2012–14 than the larger group that is the focus of this study did from 2013–15. This difference may be simply due to the compositions of the two samples.

Scores grew substantially relative to national averages.

An additional and simple way to view the effects of personalized learning is to look at the change across years of the average percentile ranks of the students relative to national norms. Chart 4 presents these results. In both cases, students were below the national median for their grade level (represented by the horizontal orange line) in the starting term and above the national median for their respective grade level two years later.

A large proportion of students with lower starting achievement levels experienced greater growth rates than peers, particularly in mathematics.

To examine how personalized learning affected students who have different academic performance levels, we conducted two analyses. First, we looked at the fraction of

CHART 2

The longer students experience personalized learning practices, the greater their growth in achievement

For 21 Schools in the Study That Implemented Personalized Learning Since 2012 or Earlier

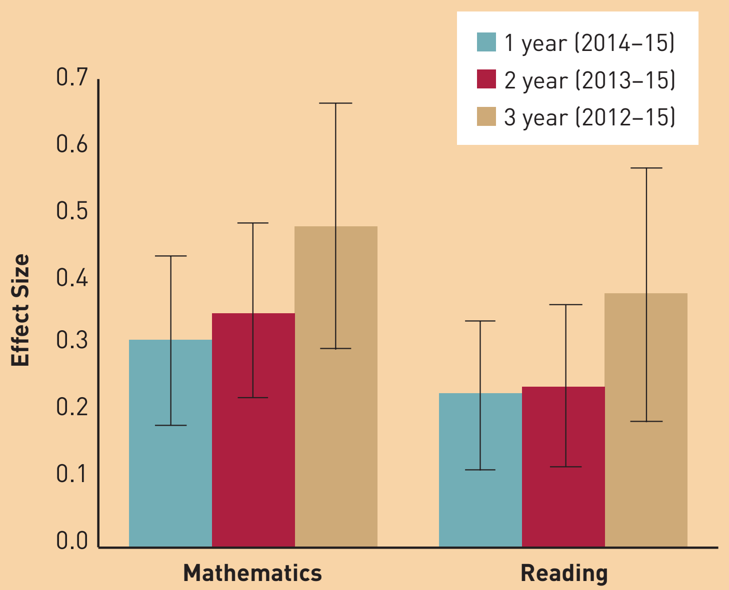
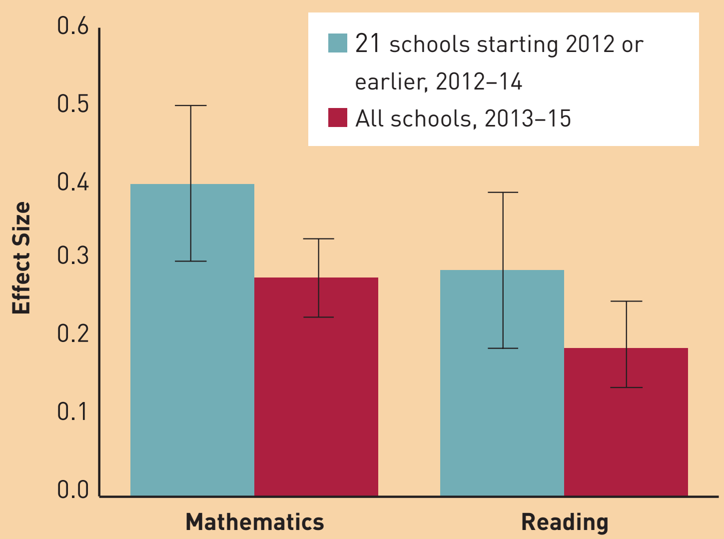


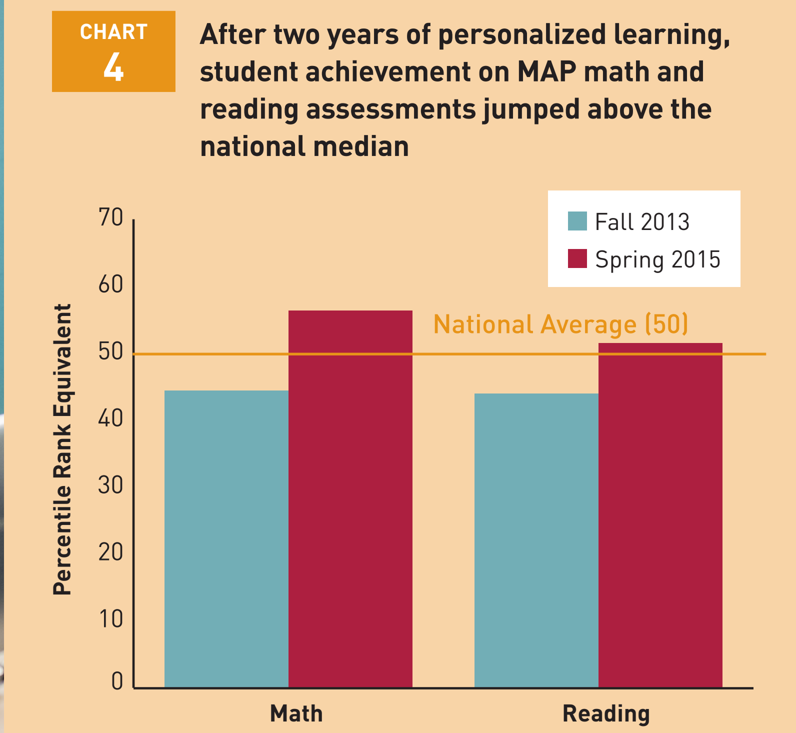
CHART 3

Effects for the 62 schools in the 2013–15 analysis are not as large as for the 21 schools in the 2012–14 analysis



	Mathematics		Reading	
Number of Students	4,506	11,217	4,757	10,906

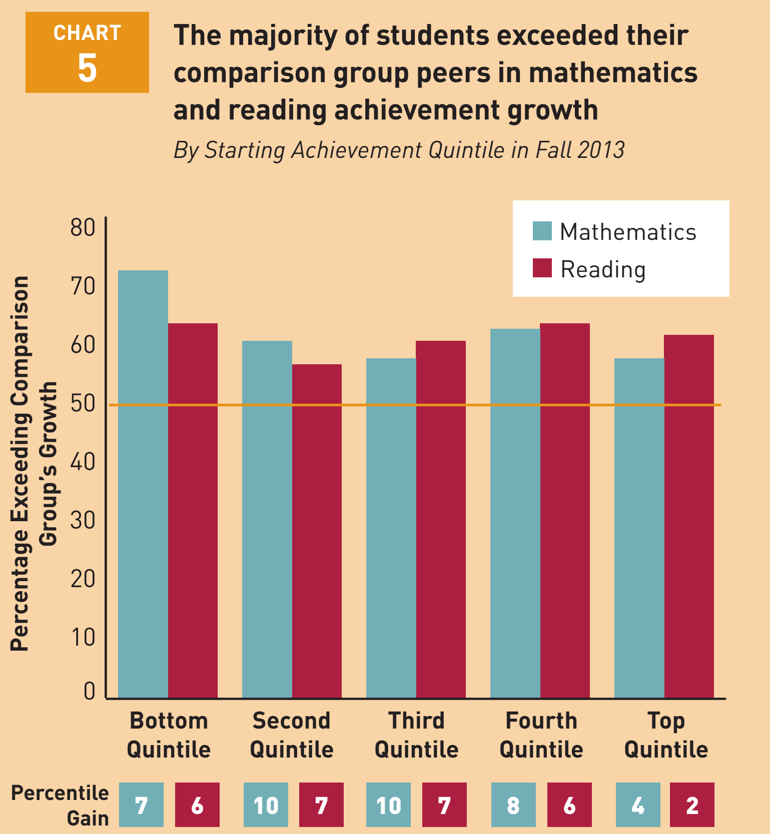
Note: All estimates are statistically significant ($p < 0.05$) after adjustment for multiple hypothesis tests.



students whose raw test score growth exceeded their VCG's raw score growth, broken up into five groups by baseline score. Chart 5 presents the results. In every case, more than half of the personalized learning students had higher growth than their comparison students. In mathematics, students with the lowest baseline scores had the greatest proportion exceed the growth of their comparison students. In the second analysis, we examine changes in percentile rank in each quintile. The percentile gains shown at the bottom of Chart 5 indicate that students in all five quintiles experienced increases in percentile rank in both subjects, that the smallest effects were in the highest quintile, and that the other four quintiles had increases of 6 percentile points or greater in both subjects.

Results were widespread, with a majority of schools having statistically positive results.

We conducted the analyses by school as well. In each subject, we included only schools for which we had data on at least 30 students. Chart 6 shows school-by-school two-year effects with the charts color-coded by grade level. Where the estimates are statistically significant, the bars are filled in solid. A majority of the schools had significant positive estimated treatment effects, with the largest effects tending to concentrate in elementary schools.

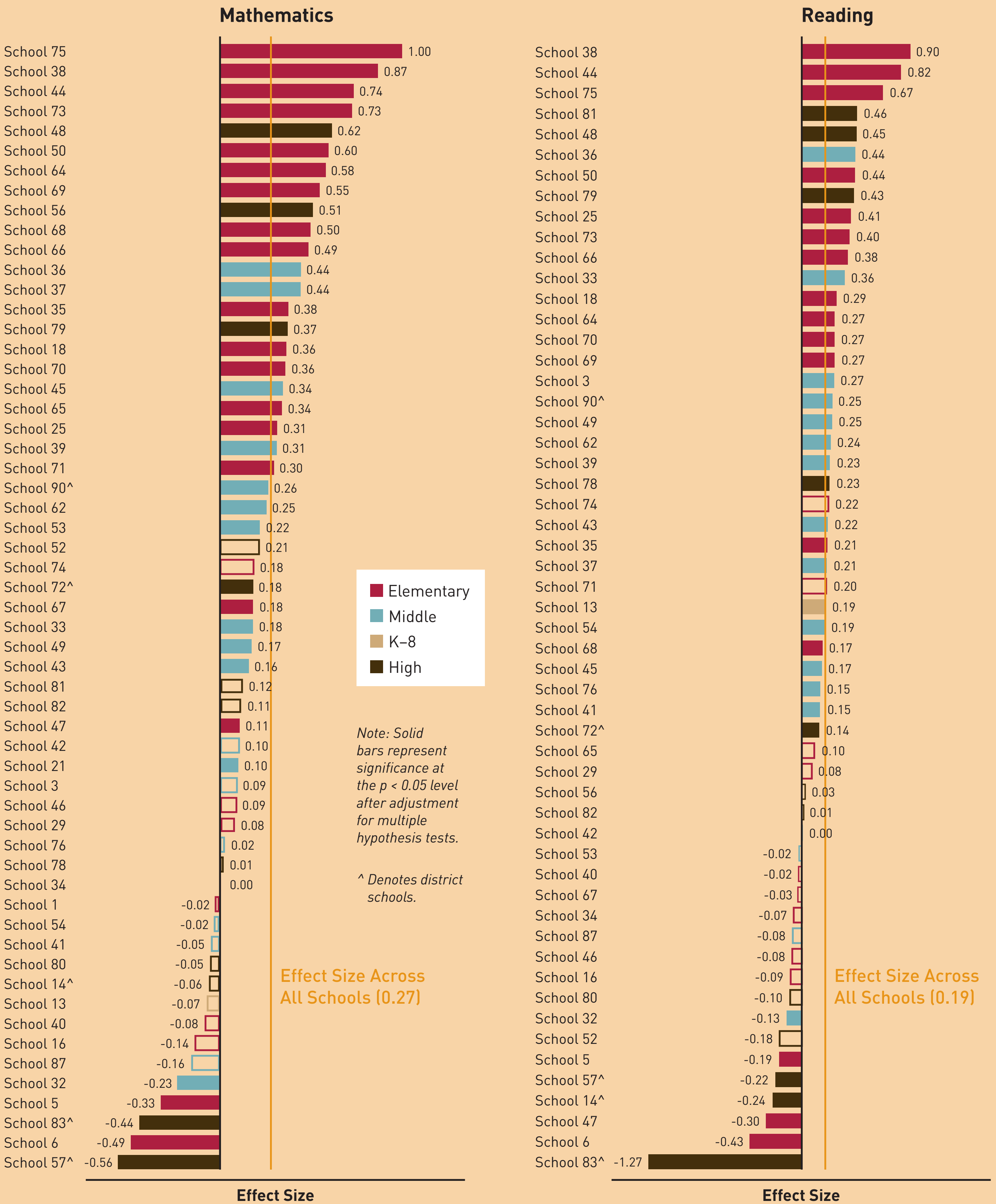


Notes: Horizontal line at 50 percent represents the expected achievement growth if there were no effect of personalized learning. Percentile gains translate the treatment effect sizes into the amount of improvement experienced by the median student in each quintile.

CHART 6

Most schools had a positive effect on students' mathematics and reading achievement

2013–15 Effect Sizes by School



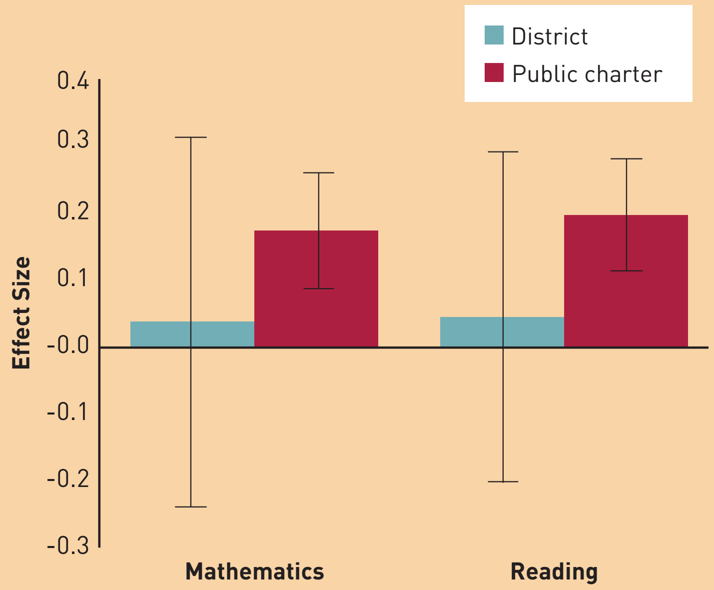
Note: Solid bars represent significance at the p < 0.05 level after adjustment for multiple hypothesis tests.

^ Denotes district schools.

District schools in the aggregate did not show significant positive effects, but the sample size was small.

Of the 62 schools in the sample, six are operated by school districts, and these schools serve grades 7–12. Chart 7 displays estimated two-year effects, which are near zero for the district schools and near 0.2 for students in the same grade range in public charter schools. Although two of the district schools produced significant positive results, this was offset by negative results in three other district schools (no school-level effect was estimated for the sixth district school because it had too few tested students). The difference in estimated effects between the district and charter schools is statistically significant; however, we caution against generalizing this result because there are so few district schools represented.

CHART 7 **Estimated effects for the six district schools in the sample and for students in the same grades (7–12) in public charter schools**



Note: Solid bars represent significance at the $p < 0.05$ level after adjustment for multiple hypothesis tests.

The findings withstand a series of rigorous sensitivity analyses.

To help evaluate the robustness of the main findings discussed in this report, we performed a variety of sensitivity analyses, including analyses based on norms, comparisons to a VCG drawn entirely from schools of choice, and analyses of the effect of test duration on results. The tests are detailed in Appendix section A1.5 and the results in Appendix section A1.6. The set of tests produced a range of estimated effects that are larger or smaller, but more often smaller, than the main results. Nonetheless, most of the estimates remained positive and statistically significant, particularly for mathematics. After evaluating the results of these sensitivity tests, we concluded that they generally support the main results presented here and the substantive conclusions we are able to draw given the limitations of the study.

Implementation Findings

Key Findings

- **Learner Profiles:** Teachers reported using a variety of data and other resources to inform their instructional decisions. While all schools used data from different sources to understand student progress, fewer reported implementation of student-centered aspects such as personalized goals and providing and discussing data with students.
- **Personal Learning Paths:** The extent to which students were able to make choices about their learning varied by course, teacher, and age of the student. Project-based learning approaches were one way of providing students with choice and with a personalized path through content. All schools provided time for individual academic support. Three-quarters of schools used a variety of instructional formats and offered out-of-school learning opportunities. Implementation of innovative out-of-school learning opportunities was limited and the opportunities offered were typically not substantially different from traditional environments.
- **Competency-Based Progression:** Students' ability to work at their own pace and advance when they had mastered the material was limited by a perceived need to emphasize grade-level content. This emphasis was driven by a desire to ensure that students were progressing toward grade-level standards and external policy constraints such as standardized testing. Fewer schools were implementing competency-based progression than were implementing other personalized learning strategies.
- **Flexible Learning Environments:** Teachers reported that the learning space was supportive of personalized learning. Most administrators reported that learning time was structured in a way that was flexible and responsive to student needs. Most schools had extended school days or school years, and the extra time was used primarily for additional instruction or to provide individualized support. Educators at many of the schools were thinking flexibly about how staff are used for instruction and student support. One-fifth of teachers reported holding unconventional roles such as co-teaching, job sharing, or working with small groups of students primarily under the supervision of another teacher.
- **College and Career Readiness:** Schools were incorporating ways to develop non-academic skills in preparation for life after high school, often through advisory curricula and cooperative learning opportunities. In addition, schools worked to develop students' awareness of postsecondary opportunities.

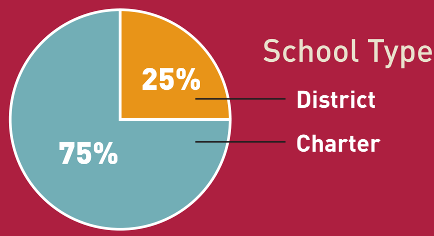
An important aim of this study is to understand how the schools implemented the five key strategies of personalized learning and how implementation varied across schools. Each strategy encompasses a set of tools and features of the personalized learning environment. Some of these, such as the provision of flexible pathways, are central to a personalized approach, whereas others (e.g., use of technology) might be viewed more as enablers of personalized learning. In this section we draw upon multiple sources of evidence—administrator interviews, student and teacher surveys, teacher logs, and school site visits—to describe the school models, focusing on implementation of each personalized learning element.

The adoption of personalized learning practices varied considerably. Personalized learning practices that are direct extensions of current practice, such as providing adequate time for individualized student support, were more common, while implementation of more challenging personalized learning strategies, such as competency-based progression, was less common.

Composition of schools in the implementation analysis

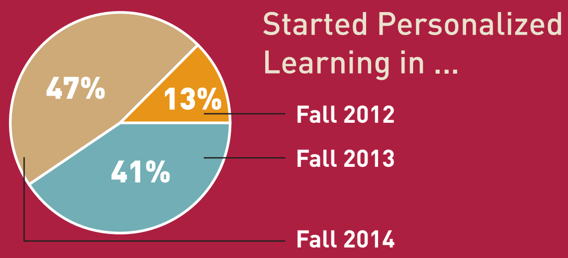
About
8,000
students

32
schools participating in Next Generation Learning Challenges

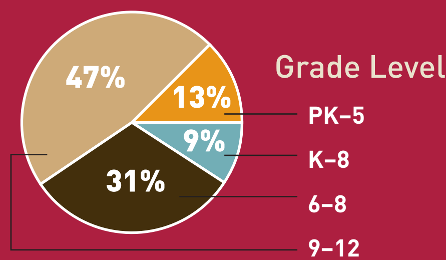


Compared with schools in the student achievement results ...

... 25% district schools vs. 10% in the achievement results



... 47% were new to implementing personalized learning in 2014 vs. none of the schools in the achievement results



... 78% are middle or high schools vs. 53% of schools in the achievement results

Note: Excludes Charter School Growth Fund and Bill & Melinda Gates Personalized Learning Pilot schools.

The implementation findings focus on 32 schools that implemented personalized learning models using funds from the NGLC program, described on page 36, and administered the MAP mathematics and reading assessments during the 2014–15 school year. The schools included in the implementation analysis are predominantly located in urban areas (two are rural) and tend to serve large proportions of minority students from low-income families. According to information provided by administrators, the school-level median of students eligible for free or reduced-price lunch is 80 percent (range: 21–100), and the school-level median of students of color is 75 percent (range: 8–100). Enrollment during the 2014–15 school year totaled approximately 8,000 students, with elementary and K–8 schools averaging about 230 students and middle and high schools averaging about 270. The grade ranges and enrollments of some schools will increase as the schools scale up to full capacity.

We drew on data from our student and teacher surveys, teacher logs, administrator interviews, and site visits to assess the extent to which elements of each of the five personalized learning strategies were being implemented, though not every data source provided information relevant to every element. Information about schoolwide implementation tended to come from administrators, who typically have greater awareness of schoolwide policies and practices than other school staff, though we did obtain some evidence of these policies and practices from teachers and students. Much of the information we obtained from teachers focused on classroom-level practices and conditions. For the most part, we found that the evidence was consistent across data sources, and that when there were discrepancies, these seemed to reflect differences in which aspect of the strategy or element the evidence addressed (e.g., principals' reports regarding opportunities for individualized instruction focused on whether time was set aside during the school day for these opportunities, whereas teachers' reports focused on their use of individualized instruction in the classroom).

Learner Profiles

KEY TAKEAWAYS

- Teachers reported using a variety of data and other resources to inform their instructional decisions.
- All administrators reported that their schools used data from different sources to understand student progress.
- About half of administrators reported that their schools were developing personalized goals for students, and two-thirds were providing data to and discussing data with students.

A key personalized learning strategy is using data—specifically, data from multiple sources, such as tests, quizzes, or projects as well as non-achievement data and learning goals—to understand student progress and inform development of personalized learning goals that are discussed with each student. Teacher survey responses suggested that teachers were not lacking student data and that a variety of data were available frequently. For example, majorities of teachers surveyed reported receiving a variety of data at least weekly, including data on:

- which students had achieved mastery (59 percent);
- which students needed extra help (55 percent); and
- which students had mastered specific concepts or skills (51 percent).

Teachers also used non-achievement data (i.e., data on student attitudes, behaviors, or motivation) frequently; about three-quarters (74 percent) of teachers reported using non-achievement data. However, 61 percent of teachers agreed or strongly agreed that while they had plenty of data, they needed help translating those data into instructional steps. Similarly, all of the administrators we interviewed reported that their schools used data from different sources to understand student progress. Half reported that their schools were implementing personalized goals for students, and two-thirds reported providing student data to students and discussing those data with them. Forty-six percent of teachers reported that their school used learner profiles.

Teacher log responses confirmed that teachers used a variety of data and other resources to inform their instructional decisions. On average, teachers reported drawing on data from formative assessments or online progress reports in 60 percent of their lessons, district or state assessments in 55 percent of lessons, and personalized student goals in 45 percent of lessons. At the same time, teachers aligned their instruction with the Common Core State Standards (75 percent of lessons) and with district and state curricula (61 percent), suggesting that teachers were attentive to grade-level expectations while also addressing individual students' needs. Together, the survey and log results suggested that despite the fact that a majority of teachers expressed a need for help translating data into instructional steps, most teachers reported using a variety of data sources on a regular basis.

Personal Learning Paths

KEY TAKEAWAYS

- Administrators reported that the extent to which students were able to make choices about their learning varied by course, teacher, and age of the student.
- Administrators and teachers identified project-based learning approaches as one way of providing students with choice and with a personalized path through content.
- All schools provided time for individual academic support, which emphasized teaching developmentally appropriate content.
- Three-quarters of schools used a variety of instructional formats and offered out-of-school learning opportunities.
- Implementation of innovative out-of-school learning opportunities was less common, and the opportunities offered were typically not technology-enabled or substantially different from traditional environments.

Personal learning paths are a central personalized learning strategy, and a key element of this strategy is providing students with flexible and multiple paths through content. One way to provide flexibility is to allow students to make choices about their learning. Where flexibility and choice were offered, they appeared to be teacher-driven rather than student-driven—on the survey, most teachers did not report high levels of student choice in content or path. Student survey data confirm this—two-thirds to three-quarters of students reported that they sometimes, rarely, or never chose what materials they used or what topics they worked on. Administrators reported that the extent to which students were able to make choices about their learning varied by course, teacher, and age of the student, with older students often being given more choice than younger students. As one administrator put it, "In general for the most part they're [students] getting told what they're working on at that point. Not that what they're being told isn't incredibly personalized, but [it's] not their own choice. It's being customized to them by their tutor." Often, schools devised strategies to offer some degree of student choice while ensuring that students were receiving instruction that was aligned to local curriculum expectations and to state standards.

Administrators and teachers identified project-based learning approaches as one way of providing students with choice and with a personalized path through content. Ideally, a project-based learning approach engages students in projects that are interdisciplinary, span several weeks or even a full semester, allow students to explore content that is interesting to them in a way that is aligned with the standards, and incorporate student choice—such as choice of content or deliverable—into the design of the project. In the spring interviews, about one-third of administrators said that their school used project-based learning as a method of instruction. Teacher survey responses suggest that project-based-learning practices were not frequently used across schools, with about one-third of teachers reporting

EXAMPLE: Interdisciplinary Project-Based Learning

In one school that is implementing a curriculum focused on project-based learning, half of the day is spent in project-based classes. The projects are interdisciplinary and emphasize skills, such as teamwork and resilience, Photoshop, sound mixing, or financial investing. Projects are often co-taught and generally span several weeks to the whole semester. In the words of one teacher:

"My projects are based on student interest so we asked, as a class, what questions we have about the world, or from current events, and then I created projects based off of that discussion. I think about what I want the final outcome to be or what I want the academic content to be along the way and I chart out some deliverables that will demonstrate learning and then I come up with resources and ideally partnerships to go along with those aims."

that these practices—projects that are interdisciplinary, extend over several weeks or months, and incorporate student input—were used to a moderate or great extent. It is important to note that two schools, which have based half of their curriculum on project-based learning, are exceptions. Interviews with teachers suggested that a challenge with employing project-based learning was similar to a challenge they encountered when implementing competency-based learning: balancing the need to teach grade-level standards with the reality that many students are unprepared for that content.

All schools set aside time to provide individual, one-on-one academic support to students—the most common were tutoring, advising, and independent work time when students could request or were given extra help.

For example, teachers at one site visit school reported that their students were engaged during their project-based learning experiences but felt challenged by the need to make sure students completed the projects and mastered the underlying standards when they had significant knowledge gaps. One teacher at this school said, "That was very hard to collaborate [to create interdisciplinary projects], not with another person but just [making sure] those standards [are addressed in the project]. And especially when there are skill deficits." Another teacher reported spending the summer designing a project for the school year but discovering in the fall that students did not yet have the necessary foundational knowledge.

According to administrators, all schools set aside time to provide individual, one-on-one academic support to students—the most common were tutoring, advising, and independent work time when students could request or were given extra help. Teacher survey responses confirmed this; nearly two-thirds (64 percent) of teachers reported that they used student achievement or mastery data to a moderate or large extent to decide which students needed individual support. Interviews with teachers and administrators suggested that the emphasis of individual supports was to help bring students up to grade level as well as to help students learn grade-level content, although acceleration beyond grade level was available for students who needed it. One administrator described it this way:

> "There's [also] the question of what are we doing once we diagnose [learning level]. If students are very significantly below grade level, they will be assessed and will receive additional tutoring to work on their weakest areas. ... Even if you are the age to be in 6th grade and reading at a first grade level, you're going to be in our English language arts/reading class, reading 6th and 7th grade texts, and participating in whole class discussions ... beyond that, there's this kind of ladder of support that are put in place to make sure our students can most succeed."

Some schools assigned staff to special roles, such as providing one-on-one support (five schools) or providing learning plans that were fully customized to each student (two schools), but approaches such as these, which are more staff- and time-intensive, seemed to be the exception rather than the rule among the schools in this sample. Many

EXAMPLE: Specialized Staff Provide Individualized Support

Guides are specialized members of staff at one of the schools who focus on the academic, social, and emotional needs of individual students. Guides make home visits and check on students multiple times in a class period. The school administrator said that most students experienced a lot of structure that was not necessarily positive in their previous schools. The role of the guide is to provide a positive structure and an example for students to follow, with the goal of helping students develop positive relationships.

students we spoke to agreed that their school provided high levels of support. As one student said, "There's a whole lot of support systems in [this school]. Everybody supports you and they look out for you, make sure that you got your head on your shoulders and you know what you're doing."

A key tenet of personalized learning is using a variety of instructional formats as a way of engaging different types of learners, which is one way schools can provide students with flexible or multiple paths through the content in a manner that suits their learning needs. More than three-quarters of administrators reported that their schools were implementing flexible or multiple paths through content. The most common instructional practices reported in site visit interviews and administrator interviews were large-group instruction, small-group instruction, and independent work, much of which was technology-led or technology-facilitated. In many schools, these strategies were used simultaneously within a class period, and students rotated among the different formats. In other schools, the strategies were used or combined as needed by the teacher in response to the requirements of the lesson or based on student data. As one teacher described it:

> **"I think that [which instructional strategies are most effective] depends on the personality of the class. Some of my classes work very well in groups and then I have one particular class [that does not do well with groups], because there would just be a lot of playing ... so I teach according to each class's personality."**

These survey reports were corroborated by the teacher log responses, which indicated that teachers varied the type of instruction based on lesson, class, or target student. Classroom observations in the site visit schools were also consistent with these reports.

Opportunities for meaningful out-of-school learning experiences are an important component of personalized learning paths. Based on administrator reports, out-of-school learning opportunities other than traditional homework for academic courses were not yet common among the personalized learning schools in our sample, even among high schools. According to administrators, there generally were not yet strong partnerships (e.g., with industry or community partners) that could be sources of internships or other out-of-school learning opportunities.

More traditional out-of-school learning experiences, homework in particular, seemed to be quite common among the personalized learning schools. Most teachers (77 percent) reported assigning homework or other out-of-school learning activities at least once a week, but only 30 percent of teachers who assigned such activities reported that they "differed from traditional homework" to a moderate or great extent. In general, students reported on surveys that:

- their out-of-school work was connected to what they were learning in school (85 percent agreed or strongly agreed);
- they were able to access the materials they needed for the assignment (84 percent); and
- these assignments helped them learn (79 percent).

Many administrators said that students were not expected to work on their technology-based schoolwork outside of school. Indeed, most administrators said that students were not allowed to take their school-issued devices home, with some citing concerns about theft or lack of Internet access at home. However, many student focus group participants reported working on schoolwork outside of school using their personal devices, which ranged from smartphones to tablets to laptops, and did not report problems with access to devices or Internet at home. These students added that, while they often did schoolwork at home, students were rarely assigned specific technology-based activities to complete at home.

Competency-Based Progression

KEY TAKEAWAYS

- Students' ability to work at their own pace and advance when they had mastered the material was limited by a perceived need to emphasize grade-level content.
- This emphasis on grade-level content was driven by a desire to ensure that students were progressing toward grade-level standards and external policy constraints such as standardized testing.
- Fewer schools seemed to be implementing the elements of competency-based progression than were implementing other personalized learning strategies.

In a competency-based model, students are placed with content that is appropriate to their learning level and are supported to work at their own pace, so they can take the time they need to fully understand the material. While many administrators mentioned that students were able to work at their own pace, many, including those who reported using competency-based systems of progression, noted that choice of pace was controlled in some way to ensure that students still made progress. Indeed, the teacher log responses suggest that on average students worked without a time limit for nearly half the lesson, but use of this approach varied by teacher and by class. Some students in three of the seven site visit schools reported varying degrees of self-pacing, but a majority of the students in these schools explained that although they were allowed to decide how to use their time, they had to meet the class deadline for the assignment. Other students at these three schools said that they were not allowed to determine the pacing of their work. As one student said:

> **"I'd say in general, whatever the teacher has you learning that week and you just have to learn it and if you fall behind, then you come after school for office hours and they'll help you out, and if you're ahead, I'm not exactly sure. Maybe the teacher might give you a couple extra things you can do, but besides that everybody, usually we're at the same pace."**

Another important factor that allows students to work at their own pace is a system in which students are able to advance (or in high schools, earn credit) when they demonstrate competency, rather than at the end of the school year; schools that are not organized by traditional grade level usually have this feature. Slightly less than two-thirds of administrators reported that their students advanced through content based on competency.

According to administrators, all but two of the 32 schools organized students using traditional grade levels. The teacher log responses were consistent with administrator reports; teachers reported that the most common way to assign students to classes is by age or grade level. However, the reality may not be as clear-cut; many administrators reported that they use a combination of diagnostic tests and their own assessments to determine where their students should be placed in the content and what types of supports they would need. Based on these reports, it seems likely that although students are organized by grade level in most schools, classroom organization is more personalized. Site visit interviews with principals confirm this hypothesis: These principals were quick to point out that although their students were placed in heterogeneous classes based on traditional grade levels, teachers used diagnostic data on student learning levels and their knowledge of students to address different students' learning needs.

As one principal said:

> "Students are organized in traditional grade levels. They're all ninth grade. We still have to communicate everything to colleges so we won't change how we have grade levels unless someone paves the way to get colleges to do things differently. We know we'll have some kids who won't be done with their courses at the end of this school year because it's competency-based, so there [may be] ninth graders coming in next year who have some tenth graders that are in [their class] finishing up freshman English. So it becomes very much more fluid as we go."

Another principal described the process for placement this way:

> "If a student is in sixth grade, we'll still put them in the sixth grade class and they'll have a sixth grade curriculum, but they will have times during the week where they can work on learning paths that are derived from their learning level according to the NWEA MAP test to help fill the gaps. The students are still placed in the grade level with students of the same age, but their content could be differentiated depending on where they test."

Because of the heterogeneous nature of classes organized by traditional grade levels, schools must address a wide range of ability levels, particularly those of students starting significantly below grade level. Despite the desire of these schools to focus on developmentally appropriate content, most schools are not truly implementing the "self-paced" element of competency-based progression. There is a perceived need to emphasize grade-level content because of externally mandated requirements for students to participate in standardized testing or meet other performance metrics. Schools try to compromise by teaching content that is at a student's learning level, as well as content that is at grade level. Most administrators reported that students can work at their own pace "to a point" but described setting a minimum pace to ensure that there was time to work through all of the required content. The result was a limit on the time students could take to master material.

Students' ability to work at their own pace and advance when they had mastered the material was limited by a perceived need to emphasize grade-level content.

Overall, it appears that schools may be implementing only some elements of competency-based instruction—such as setting a threshold for competency and trying to place students with appropriate content—that are relatively easy to implement and that don't conflict with external requirements. Policy barriers, such as state requirements for reporting student proficiency outcomes or seat time, also contribute. Indeed, several schools mentioned the particular challenge of being an innovative school in a traditional district and cited trying to implement a mastery-based system in a district that uses credits as an example. In one school, once students are enrolled in a class, they are automatically enrolled for the state exam for the course at the end of the year. This requirement inhibits implementation of a competency-based system because it puts a limit on how long students can take to work through the material. In addition, if students do not finish a course by the end of the year, that counts against the school in state accountability systems. In contrast, two school administrators mentioned a policy environment that supported competency-based progression. One school leader mentioned state legislation supporting competency-based progression and the lack of a seat-time requirement. Another administrator is located in a state that supports competency-based learning and that eased the limitations on the amount of online instruction students can receive: "Some of the new minimum standards [are] really pushing [online learning], saying that students really can learn anywhere."

Taken together, this evidence suggests that fewer schools seemed to be implementing the elements of competency-based progression than were implementing other personalized learning strategies.

Flexible Learning Environments

KEY TAKEAWAYS

- Most teachers reported that the learning space was supportive of personalization.
- Two-thirds of schools use student grouping strategies that are responsive to student needs and based on data.
- About three-quarters of administrators reported that learning time was structured in a way that was flexible and responsive to student needs.
- Most schools had extended school days or school years, and they used the extra time primarily for additional mathematics or ELA instruction or to provide individualized support.
- Educators at many of the schools were thinking flexibly about how staff are used for instruction and student support. One-fifth of teachers reported holding unconventional roles such as co-teaching, job sharing, or working with small groups of students primarily under the supervision of another teacher.
- Technology is well integrated into instruction, and most schools offered a one-to-one device-to-student ratio.

Another key attribute of personalization is the extent to which the learning environment is flexible and responsive to student needs, and resources such as staff, space, and time are used in flexible ways to support personalization. In the spring interviews, about two-thirds of administrators said that their learning space facilitated implementation of personalized learning. For example, one administrator explained that the layout of the school facilitated more structure for younger grades while also allowing for greater autonomy for older students. In this school, younger students had an assigned desktop computer, and therefore little flexibility to choose where they worked, whereas older students had laptops and could take them outside of designated classroom spaces to work. On the survey, about two-thirds of teachers reported that their school had some kind of traditional classroom space with furniture that could be moved easily; this type of space facilitated a variety of instructional strategies and could be easily rearranged to accommodate different groupings (e.g., some students could move so that they could work individually, while others worked in groups).

> *Using data to frequently adapt student grouping strategies to student needs is a key aspect of personalization; it is yet another way that instructors can be responsive to student needs and allow students to take various paths through content.*

Using data to frequently adapt student grouping strategies to student needs is a key aspect of personalization; it is yet another way that instructors can be responsive to student needs and allow students to take various paths through content. According to administrators, about two-thirds of schools used some form of flexible approach to student grouping that was informed by student needs and achievement data in at least mathematics and ELA classes. As one administrator said, "There's a lot of research on the importance of heterogeneous classes ... so [we want] to be able to keep courses heterogeneously mixed while still making sure we were meeting students' needs."

The teacher survey appears to confirm this. Three-quarters (76 percent) of teachers surveyed reported that they grouped students of similar ability levels together and about two-thirds (60 percent) of teachers who reported using flexible groupings reported changing groupings at least once a month. Similarly, teacher log responses suggest that teachers used homogeneous and heterogeneous groups for, on average, a small portion of the lesson. The variance on these items suggests that teachers used different grouping strategies across different lessons or for different students. As one teacher described it, "For me, in science I tried something that was pretty interesting, because the activities that we're doing, it really depends what I want them to be heterogeneous or homogeneous, so I set up every kid [so they could switch groups easily]."

About three-quarters of administrators reported that learning time was structured in a way that was flexible and responsive to student needs. About three-quarters of schools in the sample were implementing extended learning time for students in the form of a longer instructional day (more than 6.5 hours) or year (more than 180 instructional days). Administrators reported that most of the extra time was spent on additional instruction in mathematics and ELA or on more time to provide one-on-one support to students, generally in the form of tutoring, in all subjects. In most schools, the longer instructional periods allowed teachers more flexibility to vary the instructional strategies they used, and some administrators reported that teachers used the extra time for projects or other less traditional activities. For example, at one school with an extended day, each day contains 30 minutes of project time, 30 minutes of independent reading time, 30 minutes of mathematics practice time, time to work on personalized playlists (sets of lessons, tasks, or activities customized to each student's personalized plan), mentoring time, and peer community time. At this school, four two-week sessions expose students to enrichment and experiential learning opportunities taught by elective teachers (e.g., teachers of art or music) or volunteer instructors from the community. Teachers of core subjects (e.g., mathematics or ELA) use this time for professional development and planning. Seven schools did not implement extended learning time for students. Three of these are district schools and four are charter schools.

Educators in many of the schools reported that they were thinking flexibly about how staff are used for instruction and student support. Teachers reported a wide variety of titles on the survey, and about one-fifth (19 percent) held unconventional roles such as co-teaching, job sharing, or working with small groups of students primarily under the supervision of another teacher. Similarly, a majority of administrators reported that their models included non-credentialed instructional staff in a variety of roles. In about half of these schools, administrators mentioned that these staff are primarily responsible for supporting personalization through intervention and remediation, in roles such as tutors, instructional assistants, assistant teachers, or coaches. One school leader described a "high-dosage tutoring program at our school. It allows us to take full time tutors … and make sure every student receives individualized, intensive, small group instruction." In some

cases, such as the specialized staff described on page 18, these staff are also responsible for students' socio-emotional development. Teacher logs also suggest that staffing is flexible according to the lesson or the needs of a student; for example, many teachers reported that the number of adults in the classroom changed on a daily basis. Six administrators who mentioned utilizing non-credentialed staff said they did so to start grooming teachers; they intended that the non-credentialed role be a precursor to a full-time teaching position. A few administrators mentioned cost as a motivating factor: Their budgets did not allow them to hire as many full-time teachers as they would like, so they employed non-credentialed staff as a means of having the desired number of adults in a classroom.

Overall, technology seemed to be well integrated into instruction. Administrators reported that their schools used numerous digital curriculum programs and online resources. Most administrators said their schools used multiple software and digital resources in mathematics and ELA, and a few administrators mentioned four or five programs or resources in mathematics and an equal number in ELA. In addition, students seemed to be engaged with technology in their classrooms in a variety of ways. More than half of teachers surveyed reported that students were using technology, to a moderate or large extent, for routine tasks such as:

- using structured curriculum materials (61 percent);
- reading (57 percent);
- watching videos (57 percent);
- using online reference materials (53 percent); and
- searching for relevant materials on the web (51 percent).

Use of technology for more complex tasks was reported somewhat less frequently. These tasks include:

- solving problems or collaborating with other students from the same school (37 percent);
- use of adaptive software for problem-solving help (37 percent); and
- adjusting the parameters of simulations (20 percent).

Student focus groups confirmed that technology was most often used for routine tasks and used less frequently for more complex engagement. All administrators reported that their students had access to devices such as laptops, tablets, or in some cases, desktops. Three-quarters of administrators said that their schools had a one-to-one device-to-student ratio, and only two schools did not have devices available to all students.[2]

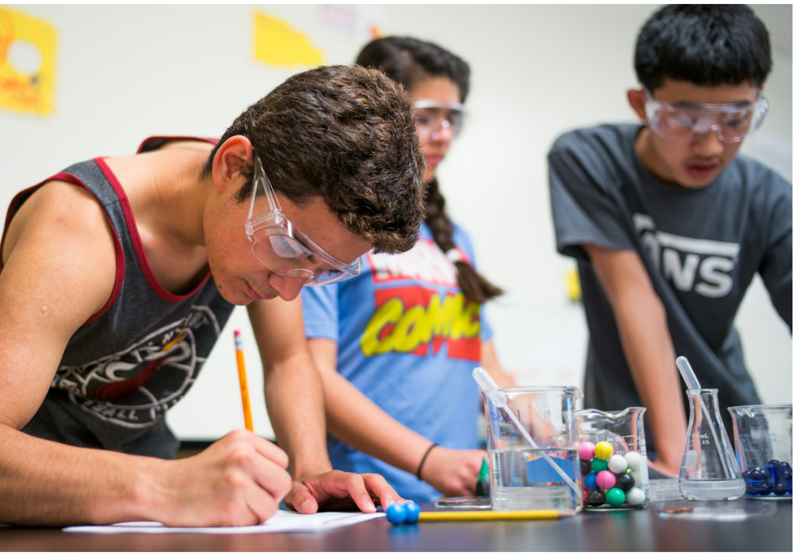
2 In 2014–15, one of these schools served only pre-kindergarten and kindergarten but planned to expand by adding a grade level each year, up to 5th grade. The second school, a high school, allowed students to bring their own devices and had a computer lab for student use but did not provide devices to all students.

Emphasis on College and Career Readiness

KEY TAKEAWAYS

- All schools were incorporating ways to develop non-academic skills in preparation for life after high school into the curriculum.
- Common approaches for addressing these skills included advisory curricula and cooperative learning opportunities, such as group projects.
- Administrators of schools at all grade levels said they were developing students' awareness of, and knowledge about, postsecondary opportunities.

Practices that promote college and career readiness are generally viewed as an important component of personalized learning. Two key aspects of college and career readiness are (1) developing the non-academic skills and competencies, such as resilience and self-reliance, which likely contribute to postsecondary success and (2) developing college and career preparation skills, such as planning which courses to take in high school or understanding colleges' admissions requirements. In the spring interviews, all administrators reported that their schools were incorporating ways to develop non-academic skills in preparation for life after high school into the curriculum in some way. Most administrators said they incorporated these skills into their advisory curriculum, and many reported that they tried to build these skills in academic classes through cooperative learning opportunities, such as group projects and other types of collaboration. A few schools were experimenting with innovative approaches, such as building these skills through a physical activity curriculum (see example on page 26) or badging programs. The few schools that did not report providing some type of support for college or career preparation were in their first year of implementation in 2014–15.



Administrators of schools at all grade levels reported providing opportunities to help students develop more traditional postsecondary preparation skills. In schools with younger students, this generally consisted of activities such as providing information about college, talking about college, and developing a belief that college is attainable. In schools with older students, these activities took the form of college counseling, college visits, and in some high schools, opportunities to earn college credit. Teacher interviews conducted during the site visits confirmed administrators' reports—most teachers listed a number of ways they were preparing students for college and career—and their responses tended to focus on activities typically offered at most schools, such as counseling.

Across schools, most of the activities that administrators reported implementing tended to focus on college and were largely similar to activities typically offered in traditional schools. Student survey responses confirm the administrator reports—across schools, half to two-thirds of students in grade 9 and above said they had visited or toured a college campus, searched the internet for college options, and met with a college counselor. Most students who participated in the focus groups agreed that their school was doing a good job of preparing them for life after high school. Students mentioned a variety of ways their schools were preparing them, such as college visits, college counseling, help with college applications, and researching colleges online. Students also discussed broader school actions, such as a curriculum that emphasizes self-direction, college readiness seminars, and dress code, as things their schools were doing to prepare them for college and the workplace.

EXAMPLE: Promoting College-Readiness Skills Through a Physical Activity Curriculum

One school is implementing a physical education and leadership class that, according to the administrators, is combined with the advisory curriculum and incorporates some academic content, most often mathematics (e.g., figuring out how long it would take to run a half mile if you run a mile in 13 minutes) and writing (e.g., journaling, in a Google Doc, about leadership goals, challenges, and accomplishments). The physical activity portion of the class is focused on building skills such as collaboration. The rationale for this course was, in the administrator's words: "We realized that students were, in an interesting sort of way … exhibiting more of a growth mindset in physical education than they were in academic education." Thus, this school chose to help students develop goal-setting, progress-tracking, and collaboration skills through this physical activity and advisory curriculum.

Contextual Factors That Influence Personalized Learning Implementation

KEY TAKEAWAYS

- Teachers expressed positive opinions about the quality of their professional development and about support from administrators and colleagues.
- A majority of administrators identified school staffing as a challenge to personalized learning implementation.
- In general, teachers were less likely to identify obstacles to using technology to support learning than they were to the effective implementation of personalized instruction.

One aspect of implementation that is relevant across the five personalized learning strategies is support for teachers. Teachers across schools expressed positive opinions about colleague and administrator support. For example, as one teacher said, "As far as the staff goes, we're very supportive. This is the best staff I've ever worked with." Another teacher described the support from her principal in this way: "[The principal is] a great buffer between the bureaucracy and teaching. In other schools you are pulled away from your teaching and you are constantly reminded of the administrative stuff you need to do and here's not like that at all. Here, we can focus on what we are doing and why we believe in it." Teachers also seemed generally satisfied with the quality and usefulness of their professional development. Half of teachers agreed or strongly agreed on a survey scale composed of positive statements about the quality and usefulness of professional development. Teachers were also satisfied with the degree of collaboration among teachers and the level of support from administrators. Eighty-five percent of teachers agreed or strongly agreed on a survey scale composed of positive statements about staff collegiality and administrator support.

At the same time, a majority of administrators identified teacher staffing as a challenge. This was particularly true for schools that opened in 2012; the administrators cited high staff turnover as a common problem. The site visit data suggested that mid-year teacher departures were disruptive, particularly in new schools, which tended to have smaller staffs. When a teacher left, other teachers often were asked to fill in until a replacement was found. Students in several of the site visit focus groups found teacher turnover to be disruptive. As one student said, "There's a lot of constant change here, I feel, with the way we learn and the teachers because maybe one week we'll have one teacher and the next week there's a different one and they have a totally different type of teaching style." In addition, the school models are so specialized and administrative and teaching staff so lean, that finding and training a replacement is not a quick process. As one administrator said, "So, qualified teachers are scarce resources … we did have a pretty high turnover rate but we also, perhaps more importantly, we did not meet with much success in finding teachers with significant experience to replace those who left."

Teachers' perceptions of obstacles to implementing technology and personalized learning practices are additional factors that could relate to implementation across the five key strategies. In general, teachers were less likely to perceive obstacles to using technology to support learning than they were to the effective implementation of personalized instruction. For example, in the survey, majorities of teachers reported they were well supported in using technology for student learning, had flexibility and input into how it was implemented, and were confident in their own technology skills; lack of high-quality content was not perceived as an obstacle by most. Teacher log responses are consistent with the survey reports—most barriers were infrequently reported, and when reported, they seemed to vary by class or by student.

Although about half of the teachers surveyed reported that obstacles to implementing personalized learning either did not exist in their school or were not an obstacle if they did exist, some teachers identified obstacles. Student characteristics, such as too much diversity in achievement levels, high levels of disciplinary problems, absenteeism, and large class sizes were minor or major obstacles mentioned by one-third to one-half of teachers. Time demands—both the time to develop personalized content and time to develop personalized lessons—were noted as obstacles by one-half to two-thirds of teachers, with 50 percent saying the time required to develop personalized content was a major obstacle. Pressure to cover specific material for testing or other requirements was a minor or major obstacle for 40 percent of teachers.

Relating Implementation to Outcomes

Key Findings

- **No single element of personalized learning was able to discriminate between the schools with the largest achievement effects and the others in the sample; however, we did identify groups of elements that, when present together, distinguished the success cases from others.**
- **Three personalized learning elements—Student Grouping, Learning Space Supports Model, and Students Discuss Data—had the greatest ability to isolate the success cases from the other schools. All of these elements were being implemented in the most successful schools.**

We conducted additional analyses to explore whether particular elements of the five personalized learning strategies, alone or in combination, appear to be associated with positive effects on student achievement outcomes.

To analyze which elements of the five personalized learning strategies were most strongly related to positive effects on student achievement, we focused on 32 schools for which both implementation data and assessment data were available for the 2014–15 school year.

First, we tabulated 14 variables for each school: 13 elements of personalized learning and one administrative feature. The 13 elements of personalized learning are components of the five key personalized learning strategies described earlier in this report. Specifically, learner profiles (two elements), personal learning paths (three elements), competency-based progression (two elements), flexible learning environment (five elements), and college and career readiness (one element); the full list of elements and their definitions are listed in Appendix 5. Each variable captures whether each school showed evidence of implementing the element, based on the administrator interview and teacher and student survey data. The administrative feature is whether the school is a district or public charter school. We coded each variable as zero (i.e., did not show evidence of implementation) or one (i.e., showed evidence of implementation). Every school in this dataset has a unique combination of elements, but together they represent only a very small fraction of the more than 16,000 possible combinations of 14 binary variables.

We applied a method called qualitative comparative analysis (QCA) (Ragin, 1987) to look for patterns of elements that were implemented in the most successful schools. We explored a variety of definitions of success and found that the method produced meaningful results when we set a relatively high bar: schools with estimated treatment effects that were statistically significant and larger than 0.2 in both mathematics and reading. Five of the 32 schools (16 percent) met this criterion for success and have the following attributes: Four are charter schools, and one is a district school; one is a high school, two are middle schools, and two cover a broader secondary grade range. For the purposes of this section only, we refer to these five as successful, recognizing this sets a high bar for success and that additional schools in this sample could arguably also be considered successes.

No single personalized learning element distinguished the successful schools from others in the sample; however, QCA did identify groups of elements that, when present together, distinguished the success cases from others. The three identified patterns are shown in Table 1.

Student Grouping (present in all three patterns) and Learning Space Supports Model and Students Discuss Data (each present in two patterns) are highlighted in the table because they have the greatest ability to isolate the successes from the other schools. In pattern 1, the three variables are sufficient. In patterns 2 and 3, two of the variables are sufficient to identify the successes but in each case also include one school that is not in this most successful group. In those patterns a third variable is necessary to exclude that remaining school. For interpretation, we focus on these three variables because they are sufficient to isolate the success cases (pattern 1), and the ability of the other two variables to exclude single schools in patterns 2 and 3 may be coincidental.

Three elements of personalized learning were being implemented in tandem in the schools with the largest achievement effects, and these features were not all present together in any of the other schools in the sample: Student Grouping, Learning Space Supports Model, and Students Discuss Data.

Together these elements support aspects of the learner profiles and flexible learning environment strategies. Student grouping seems particularly important because it is present in all three patterns. To credit a school as implementing this element, we looked for grouping strategies driven by data and that were dynamic, flexible, and responsive to student needs. Data use is also an important element for implementing the Students Discuss Data element. To credit a school as implementing this element, we required that student data be provided to students and for them to be included in discussions such as how the data relate to the students' personal learning goals. This may work to enhance the effectiveness of student grouping if students have a greater voice in the formation of the groups and the activities the groups undertake. Finally, when schools use grouping, it may be particularly important to operate in a learning space that supports, or does not hinder, the use of this strategy. For example, grouping strategies are likely to require audible interactions, and if several groups attempt to operate

Table 1: Patterns of elements in the most successful schools

	Student Grouping	Learning Space Supports Model	Students Discuss Data	Outside of School Learning	Individual Support
Pattern 1	✔	✔	✔		
Pattern 2	✔	✔		✔	
Pattern 3	✔		✔		✘

Note: ✔ indicates element is present; ✘ indicates element is absent. Shaded portion of table highlights the variables with the greatest ability to discriminate the success cases from the other schools.

together in a learning space, the noises or activities of adjacent groups may be a distraction.

In summary, we identified three elements of personalized learning that were being implemented in tandem in the most successful schools in the sample, and these elements were not all present together in any of the other schools in the sample. This suggests that, among the many elements of implementing personalized learning, these may be particularly important. However, caution is warranted because our sample is very small relative to the very large space of possible combinations of features. It is also possible that the variables available in our data and included in this analysis do not capture all the possible personalized learning elements and that we may have inadvertently omitted elements that are important for explaining success. Moreover, these results may be sensitive to errors in the coding of elements, which relied on self-report interview and survey data and thus are subject to the limitations of those data sources discussed. Finally, this is a correlational analysis, and so the results and interpretation should be viewed as exploratory or hypothesis generating, rather than confirmatory.

National Comparison of Survey Results

We compared the teacher and student survey results from the 32 schools in our implementation analysis to results from Grunwald Associates' administration of nearly identical questions to a national sample of teachers and students. The national results are intended to provide context for the findings from the personalized learning schools to help understand the ways in which the experiences of students and teachers in these schools differed from the experiences of students and teachers nationally.

To facilitate this comparison, we first weighted the national survey results to more closely reflect the personalized learning sample in terms of geographic locale (e.g., urban), grade level, subject taught (by teachers), and gender (of students). However, we lacked the necessary data to include family income in the student survey weighting process, and the national sample appears to be somewhat more affluent than the personalized learning sample. Moreover, the personalized learning surveys were conducted in the spring, and the national surveys were conducted in the summer. For a complete list of items and constructs compared across samples, refer to Appendix 3 for the student survey and Appendix 4 for the teacher survey.

In general, teacher survey responses between the two samples were consistent in several areas. For example, teachers in both samples had positive opinions of their professional development opportunities, and about 60 percent of teachers in both samples agreed or strongly agreed that their students were respectful and motivated. Forty-five percent of teachers in both samples reported

Key Findings

- Teachers in the two samples reported similar use and characteristics of learner profiles and similar emphasis on student choice.
- Personalized learning teachers were more likely than those in the national sample to use technology for personalization and to report use of instructional practices that support competency-based learning.
- Personalized learning teachers were more likely to agree or strongly agree that their schools' data system was useful.
- Students in both samples agreed or strongly agreed that there was an emphasis on making them aware of instructional goals and tracking progress toward mastery.
- Personalized learning students were more likely to report that their mathematics and ELA instruction incorporated aspects of complex, student-centered instruction most of the time or always.

How Survey Responses Are Summarized in This Section

The analysis in this section relies on survey scales, which are groups of items that address a higher-level construct. The scales are defined in Appendices 3 and 4. For this comparison, we calculate the proportion of respondents whose scale average is in the positive range of response options (for example, agree or strongly agree).

that the learner profiles used in their schools shared similar characteristics (e.g., that they existed for every student; were routinely accessed by students and staff; were frequently updated; and summarized students strengths, weaknesses, goals, and aspirations to a great or moderate extent). About one-third of teachers in both samples reported emphasizing student choice (e.g., choices of instructional content or materials) to a great or moderate extent.

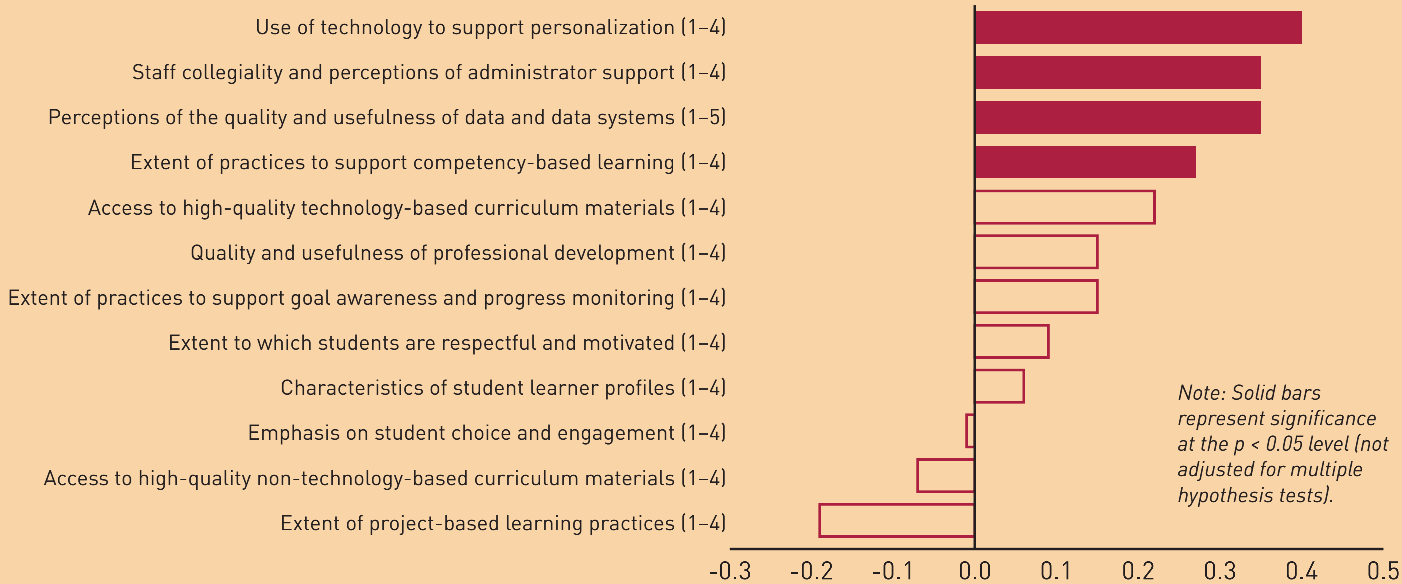
There were significant differences in teacher responses to questions about staff collegiality and perceptions of administrator support, perceptions of the schools' data systems, use of instructional practices that support competency-based learning, and use of technology to support personalization. Teachers in personalized learning schools were more likely to agree or strongly agree that they worked in an environment where they felt supported by their colleagues and administrators, to agree or strongly agree that their schools' data system was useful, and to report that they used instructional practices that support competency-based learning to a moderate or large extent.

On the student surveys, in general, there were more differences than similarities in responses between the two samples. Students in both samples agreed or strongly agreed that there was an emphasis on making them aware of instructional goals and tracking progress toward mastery, that they were able to get help quickly, that there were opportunities to practice material, and that they were

CHART 8

Teachers at personalized learning schools differed from a national sample in their use of some practices

Difference Between Schools Implementing Personalized Learning in Spring 2015 and National Sample in Summer 2015

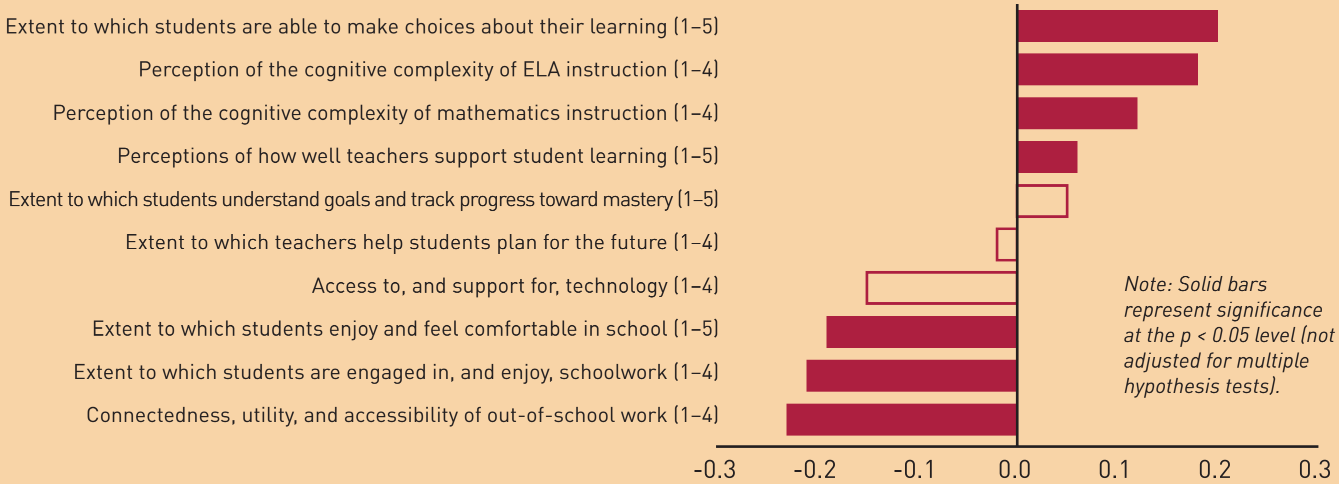


Note: Solid bars represent significance at the $p < 0.05$ level (not adjusted for multiple hypothesis tests).

CHART 9

Students at personalized learning schools reported perceptions that were generally different from a national sample of students

Difference Between Schools Implementing Personalized Learning in Spring 2015 and National Sample in Summer 2015



required to demonstrate understanding before moving on to a new topic. In addition, slightly more than two-thirds agreed or strongly agreed that teachers helped them plan for the future.

The two samples differed in their perceptions of some instructional elements, such as student choice and aspects of mathematics and ELA instruction. Students in the personalized learning schools were more likely than students in the national sample to report that they were able to make choices about their learning most of the time or almost all of the time and that their mathematics and ELA instruction incorporated aspects of complex, student-centered instruction (e.g., discussion and debate, working with partners, and engagement with complex tasks) most of the time or always. They were also less likely than students in the national sample to indicate that the out-of-school work they received helped them learn, was accessible, and was connected to what they were learning in school.

In summary, teachers in personalized learning schools appeared to have better technology and data systems to support personalization and were implementing instructional practices that support competency-based learning more than teachers in the national sample. This was true even though competency-based practices were less prevalent in personalized learning schools than some of the other strategies. Students in personalized learning schools

reported a greater degree of choice and teacher support and mathematics and ELA instruction that was more cognitively demanding, but they also reported less enjoyment of school and schoolwork.

Conclusions

These findings are largely positive and promising. They indicate that compared to their peers, students in schools using personalized learning practices are making greater progress over the course of two school years and that students who started out behind are now catching up to perform at or above national averages.

Although implementation of personalized learning varied considerably across the 32 schools in the implementation analysis, our findings suggest that the schools are employing a number of practices that support personalization. Teachers at most schools are using data to understand student progress and make instructional decisions, all schools offer time for individual academic support, and the use of technology for personalization is widespread. However, some strategies, such as competency-based progression, were less common and more challenging to implement. The schools that exhibited the greatest achievement growth were all implementing three personalized learning features—student grouping, learning spaces that support personalized learning, and opportunities for students to discuss their learning data with teachers.

We find overall positive and large student achievement gains from personalized learning exposure. These results are robust to most of our sensitivity analyses, especially for mathematics. The results are substantially heterogeneous across schools, with fewer schools seeing very large gains, and some seeing no or even negative effects from personalized learning. The gains are largest for lower grades, but this is also where students typically experience larger achievement gains overall. Students in the lowest baseline score quintile seem to be affected the most. While our results do seem robust to our various sensitivity analyses, we urge caution regarding interpreting these results as causal. While we implemented the best estimation strategies possible given the nature of the data and the lack of opportunity to implement a strong experimental design, we were unable to separate actual school effects from the personalized learning effects. In other words, those schools that were awarded the grants to implement personalized learning might be better at teaching their students, regardless of whether personalized learning was implemented. If this is true, then our results would be a combination of the personalized learning treatment effect and the school effect and would overestimate the effects of the personalized learning intervention. Still, we feel that these findings suggest the impact of personalized learning and its effects on student achievement are promising.

RAND will produce a more comprehensive report with additional details in 2016.

Participating Initiatives

The Next Generation Learning Challenges (NGLC) initiative supports school districts, charter management organizations, and partner organizations that embrace personalized learning as a means to dramatically increase college readiness rates, particularly among low-income students and students of color.*

The NGLC investments are focused in three areas:

- Catalyzing innovation in school design, aligned with principles of personalized learning
- Collecting and sharing evidence of promising practices and lessons learned
- Fostering communities of innovators and adopters of personalized learning practices

To be considered for funding, these schools applied for a competitive grant via a "wave" of funding designed and organized by NGLC. In their application, schools were required to describe with specificity how their models would support personalized learning. While all of these schools have a high degree of integrated technology as part of their school designs, they vary considerably in the methods and degrees to which they use technology to support personalized learning.

** The NGLC initiative is managed by EDUCAUSE, a nonprofit association dedicated to advancing the use of information technology in higher education, in association with other organizational partners including the League for Innovation in the Community College, the International Association for K–12 Online Learning, and the Council of Chief State School Officers. NGLC receives primary funding from the Bill & Melinda Gates Foundation, with additional support from the William and Flora Hewlett Foundation, the Eli and Edythe Broad Foundation, and the Michael and Susan Dell Foundation.*

The Charter School Growth Fund (CSGF) Identifies the country's best public charter schools, funds their expansion, and helps to increase their impact. As a national nonprofit, CSGF makes multi-year, philanthropic investments in talented education entrepreneurs building networks of great charter schools and provides them with support as they grow.

To date, CSGF has funded the expansion of charter school networks across 23 states in a wide range of communities, ranging from Los Angeles and Phoenix to the Rio Grande Valley and Mississippi River Delta. The CSGF "portfolio" includes 50-plus organizations operating 500-plus schools and serving more than 250,000 students—75 percent of whom are low-income students and 90 percent of whom are students of color. These schools are transforming lives and proving that meaningful and lasting improvement is possible in K–12 education. The CSGF portfolio is collectively opening more than 70 new schools that enroll 40,000 additional students each fall and have sent more than 22,000 students to college—a number expected to rise tenfold by 2025.

A key strategy of CSGF's work is to invest in organizations that are developing "next-generation" schools, which are pioneering new ways to personalize learning and improve student outcomes. In just five years, CSGF has committed nearly $30 million to 23 next-generation charter school networks and entrepreneurs.

The Bill & Melinda Gates Foundation's Personalized Learning Pilots is a three-year initiative, which began in 2012, to deepen and expand personalized learning in a set of schools from high-performing public charter school networks. The financial support was intended to help the schools integrate personalized learning strategies more deeply into instruction at the classroom and/or schoolwide level. If the early evidence was positive, the foundation expected that these schools would eventually expand the use of personalized learning to additional schools within their networks.

The foundation awarded grants to schools through a series of competitive selection processes. Schools that applied were asked to describe their vision for integrating personalized learning into core literacy and/or mathematics instruction; demonstrating innovative uses of human capital, time, and space; and adopting competency-based progression, which allows and encourages students to advance through content and earn credit (if applicable) based on demonstrating adequate mastery of knowledge and skills.

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Acknowledgments

The authors are grateful to the personalized learning students, teachers, and administrators who voluntarily participated in project data collection; NGLC staff who facilitated connections with the schools; and NWEA staff who responded to our multiple requests for assessment data and helped us interpret the data. We are also grateful to the following RAND staff who contributed to the research: Mollie Rudnick, Courtney Kase, Amanda Edelman, Andrea Bingham, Katharina Best, Christopher Paul, Evan Peet, Kyle Siler-Evans, Gerald Hunter, Melanie Rote, Suzette Gambone, and Stephanie Lonsinger. This document is vastly improved as a result of feedback we received on earlier drafts from: Cathy Stasz, Julia Kaufman, Patrick McEwan, Betheny Gross, Jon Fullerton, Robert Murphy, Tung Le, Andy Calkins, Heather Fox, and Brad Bernatek and his colleagues at the Bill & Melinda Gates Foundation. KSA-Plus Communications provided editorial assistance and design. Any flaws that remain are solely our own responsibility.

APPENDIX 1 Methods for Achievement Analysis

A1.1 Numbers of Schools and Students in Achievement Analysis Samples

Table A1 displays the number of personalized learning schools and students entering into overall analyses of mathematics and reading for the 62 schools that are the main focus of the analysis, as well as the smaller group of 21 schools that implemented personalized learning over a three-year span.[3] Students had to remain in one of the personalized learning schools in our sample to be included in the analyses. This explains reduced numbers or zeros near common boundaries of school grade configuration.

Table A1: Numbers of personalized learning schools and students in aggregate analyses

		Subject	N schools	N students by their grade level in 2015: 1	2	3	4	5	6	7	8	9	10	11	12
2013–15	Charter Schools	Mathematics	57	1,662	1,834	1,506	1,260	519	962	1,257	811	83	446	67	30
		Reading	56	1,639	1,776	1,483	1,287	469	923	1,174	745	79	498	72	
	District Schools	Mathematics	5							189	146	107	359	10	6
		Reading	5							185	141	67	362	6	1
2012–15	Charter Schools	Mathematics	21		869	814	716	251	22	358	435			82	16
		Reading	21		865	815	710	247	22	358	439			146	3

A1.2 Matching Method for the VCG

For each treatment student, NWEA created a VCG of up to 51 students from its database. Separate comparison groups were created for the mathematics and reading tests and for each time span examined. The analysis used fall scores as pretest and spring scores (two years later for two-year analysis, three years later for three-year analysis) as the post-test. NWEA's standard student and school matching criteria were applied to create the VCG.[4]

REQUIREMENTS FOR ALL VCG MATCHES

- Students have valid scores for the pretest and the post-test.
- Students are not in the same school district as the treatment group students.
- Schools have the same locale classification (e.g., urban, suburban, rural, etc., according to the National Center for Educational Statistics Public School Universe Survey).
- Students are the same gender and in the same grade as the treatment group students to whom they are matched.

APPROXIMATE MATCHING CRITERIA

- Schools differ by no more than 15 percentage points on the portion of students participating in the national free or reduced-price lunch program.
- Students scored similarly on the pretest MAP assessment. Preference is given for students with the exact same pretest score, but this can be expanded to within five points on NWEA's RIT scale if necessary to find matches.[5]
- Number of days elapsed between the pretest and post-test testing differs by no more than 18.

Notably, NWEA's testing database does not contain any additional student-level covariates that could have been used in the matching process or in statistical models for analysis.

3 A school was excluded from school-level analyses if data were available for fewer than 30 students, but those students and schools were included in aggregate analyses and in Table A1.
4 NWEA first identified all student records that met these criteria, and if there were more than 51, then took a random sample of 51 of those records.
5 NWEA's RIT (Rasch Unit) scale is a stable equal-interval vertical scale designed to allow items of different difficulty levels to be placed on a common scale. A student's RIT score indicates the level of question difficulty a given student is capable of answering correctly about 50 percent of the time.

A1.3 Assessment of Balance Between the Treatment Group and the VCG

The VCG is intended to be very similar to the study group in terms of students' observable characteristics prior to treatment. This is true by construction for the criteria that were matched exactly (namely, the grade level of the student and the urbanicity of their school). For remaining variables, we examined whether the groups appear to be the same, controlling for the grouping of each study student with up to 51 VCG students (on average, personalized learning students were matched to 50 VCG students, with more than 95 percent of the students being matched to a full set of 51 VCG students). Table A2 shows balance on variables that were not exactly matched. In both mathematics and reading, very close matches were achieved on the starting MAP scores. The school percentages of students eligible for free or reduced-price lunch were about 1–2 percent lower in the VCG. The number of days between the pretest and post-test assessments was about two to six days longer for the personalized learning students than for the VCG students. Because free or reduced-price lunch is not exactly balanced between groups, we included it as a covariate in outcomes models. The imbalance in elapsed time between pretest and post-test also was accounted for in the estimation strategy (described below) by using growth per day as the outcome.

Table A2: Balance between personalized learning groups and VCGs on available covariates

Timespan	Subject	Variable	VCG mean	VCG SD	Personalized learning mean	Personalized learning SD	Difference	Standardized difference
2012–15	Mathematics	RIT	180.39	30.46	180.41	32.18	-0.02	0.00
	Mathematics	FRL	84.88	16.27	82.73	14.27	2.15	0.13
	Mathematics	time	985.79	23.75	990.18	24.79	-4.39	-0.18
	Reading	RIT	175.45	28.92	175.45	30.97	0.00	0.00
	Reading	FRL	83.75	16.00	81.70	15.76	2.05	0.13
	Reading	time	984.39	22.57	990.13	24.26	-5.75	-0.25
2013–15	Mathematics	RIT	186.89	31.42	187.54	31.79	-0.64	-0.02
	Mathematics	FRL	81.64	15.61	80.87	15.63	0.77	0.05
	Mathematics	time	608.99	26.66	611.34	27.97	-2.35	-0.09
	Reading	RIT	182.37	29.24	184.35	30.26	-1.99	-0.07
	Reading	FRL	81.57	16.03	80.80	16.42	0.77	0.05
	Reading	time	609.28	26.49	611.78	28.11	-2.50	-0.09

Note: RIT is the score on the MAP assessment, FRL is the school percentage of students eligible for free or reduced-price lunch, and time is the elapsed time between pretest and post-test.

A1.4 Details and Limitations of the Statistical Estimation Strategy

To analyze the effect of attending a personalized learning school, we fit statistical models that account for clustering of students within schools and of each student with his or her VCG of up to 51 students. The dependent variable in this model is the gain from pretest to post-test in the MAP assessment scale score. We standardized test scores using mean and standard deviations of the pretest scores by grade, so that the pretest scores have a mean of zero and standard deviation of one within each grade level, and post-test scores reflect the standardized growth. For the baseline model, we then divided the standardized growth by the number of days elapsed between pretest and post-test, to account for variation in the time elapsed, to obtain a standardized measure of growth in achievement per day. We also controlled for the percentage of students eligible for free or reduced-price lunch. We then demeaned the variables by VCG group to account for all factors that make a treated student similar to his or her matched VCG, including the observed list of matching variables described above. We regressed the demeaned standardized growth in achievement per day on demeaned treatment status and demeaned percentage of students eligible for free or reduced-price lunch. We scaled the treatment effect back up to a year by multiplying the coefficient on treatment by the average number of elapsed days for the data (treatment and control). We clustered the standard errors at the school level and adjusted the degrees of freedom to account for the demeaning. Given the within-VCG estimation strategy, none of the exactly matched covariates can be included in the regression but are implicitly controlled for by the estimation strategy.

Although the analysis of MAP using VCGs is the most rigorous method available, it relies on the matching of students within our sample to similar students outside the sample. Because students in treatment schools may differ from their comparison groups in unobserved ways that affect their academic performance, this method is vulnerable to selection bias even if matches appear to be very good on observable characteristics. Any unmeasured differences between the study sample and the comparison group can result in biased estimates of treatment effects. Also, this analysis implicitly assumes that VCG students are in more traditional schools that are generally not implementing personalized learning innovations. There is no way to verify this assumption. To the extent personalized learning is actually more widespread in VCG schools, the contrast between treatment and VCG instruction would be reduced and the analysis would underestimate the effects of personalized learning.

Because of these limitations, achievement results should be interpreted with some caution.

A1.5 Sensitivity Analyses

To help evaluate the robustness of the main findings discussed above, we performed a variety of sensitivity analyses. The extent to which these alternative analyses produce similar or different estimates than our main analyses can help validate the treatment estimates or place likely bounds on true treatment effects.

ANALYSES BASED ON NORMS

First, we used an alternative method for estimating treatment effects using conditional expected growth estimates based on norms (CGN) calculated by NWEA. CGN uses students' starting scores and elapsed time to predict a typical post-test score based on normative data from a national sample (for more on the CGN methodology, see NWEA, 2011, pages 245–7). The CGN method does not consider other factors that are part of the VCG matching, such as student gender, schoolwide measures of poverty (free or reduced-price lunch), and geographic locale. NWEA only calculates single-year growth norms, so we scaled up the single-year estimates for each student to the appropriate number of years.[6] For each relevant subgroup (school, grade span, or overall), we estimated the average difference between the treated students' realized growth and the conditional growth estimates, under the assumption that national norms generally represent typical growth in schools that are not personalized learning schools.

SCHOOLS OF CHOICE VCG ANALYSES

In a second sensitivity analysis, we set additional constraints for the VCG matching. Many of the personalized learning schools are schools of choice, which may tend to enroll a select group of students. As one example, families make an affirmative decision to enroll their children. Family involvement in education might influence student achievement in positive ways unrelated to the school's influence on achievement. To the extent VCGs are drawn from schools that are not schools of choice, there is the potential that a difference in family involvement or other factors that might influence students to enroll in schools of choice could bias the results. We investigated this concern by attempting to make the treatment and control groups more similar on such factors. We asked NWEA to create an additional VCG for each treated student, supplementing the matching criteria with the additional restriction of drawing only from other schools of choice, which NWEA defined as charter, academy, private, magnet, and parochial schools. We compared the treatment effect estimate using the schools of choice VCG to that from the standard VCG matching criteria that ignore choice. The concern about unmeasured differences between choice and non-choice schools would gain credence if the schools of choice VCG produce meaningfully lower treatment effect estimates than the standard VCG analysis.

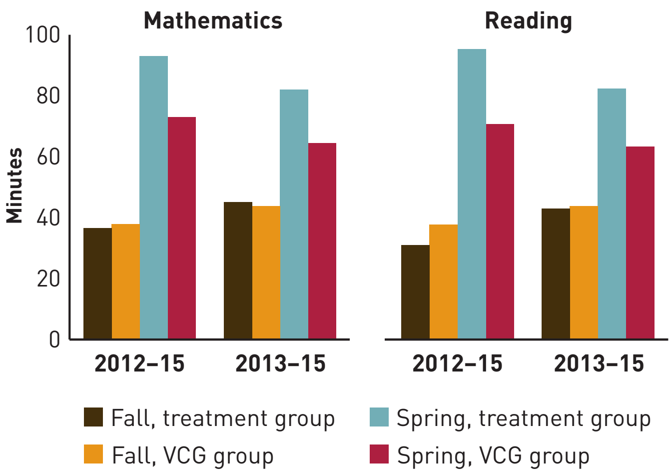
6 To create these scaling factors for each grade and subject we used the national norms for average RIT score growth in one academic year and contrasted this with the average growth in multiple years.

FILTERING AND ALTERNATIVE TIMESPAN ANALYSES

Finally, we discovered anomalous patterns in test duration (the amount of time students spend taking the test) among students and schools in the study. Briefly, some student test events had very long durations or large changes in test duration between the fall pretests and spring post-tests. This raised concerns that differences in duration, or testing conditions that drive changes in duration, might influence estimates of the treatment effect of attending a personalized learning school.

To that end, we performed a set of sensitivity analyses related to duration to gain a better understanding of how anomalies in test duration might be affecting treatment effect estimates. We applied filters to remove students with anomalous test durations or anomalous changes in test duration between pretest and post-test. We also applied filters at the school level based on aggregate patterns of test durations of the participating students. Finally, we examined the use of different timespans such as fall-to-fall or spring-to-spring because these pretest/post-test pairs tend to have less discrepancy in test duration. Chart A1 shows that while the treated students and their VCGs took approximately the same amount of time on the fall test, the treated students took substantially longer on the spring tests.

Chart A1: Test durations for personalized learning and VCG students



We tested a number of filters to address and understand the effect of anomalous test duration growth on the estimated treatment effects. First, we began by filtering out odd test durations both among the treated students and the VCGs. We used the following filters:

Filter 1: Drop if fall or spring test durations are below 5th percentile or above 95th percentile for grade and subject (national duration, provided in personal communication by NWEA).

Filter 2: Drop if the change in test duration from fall to spring exceeds the national 90th percentile of change in test duration for grade and subject.

Filter 3: Drop if the durations meet the criteria of both filter 1 and filter 2.

If a personalized learning student met a filter's criteria, all of the VCG records for that student were also filtered out. However, if a VCG student was filtered, we did not drop the corresponding personalized learning student or other VCG records that did not meet filter criteria. Table A3 presents the fraction of treated and VCG students that are filtered out by the various filters. In every case, more treatment students are filtered than VCG students. Filter 3 (by construction) filters out the smallest fraction of students.

Table A3: Percentages of personalized learning and VCG students dropped by filters

		Filter 1		Filter 2		Filter 3	
Timespan	Subject	PL	VCG	PL	VCG	PL	VCG
2012–15	Mathematics	51%	31%	47%	28%	40%	21%
	Reading	53%	33%	50%	23%	42%	17%
2013–15	Mathematics	42%	26%	39%	21%	30%	14%
	Reading	43%	26%	40%	21%	30%	13%

Although some changes in test duration could reflect inappropriate test administration conditions, in some cases these changes might be due to factors that could legitimately be attributed to treatment effects, such as academic growth that results in more difficult (and more time-consuming) items being administered in the spring or increases in students' willingness to persist through challenging test content. Where this is the case, it would be incorrect to filter such students out, and the treatment effect would be biased if part of the treatment were increasing student human capital in these ways that would appear to result in anomalous test duration or change in duration. To that end, we additionally evaluated the overall treatment effect where instead of filtering individual students out, we only filtered out anomalous schools. We used two methods to filter out schools:

- Calculate average durations by subject and grade for all students in the school and filter out the school if filter criteria are met.

- Filter out a school if more than 40 percent of students in that school meet filter criteria.

Using these filtered datasets, we applied the same statistical models used previously to estimate treatment effects overall and for each school, for each subject and timespan.

As an alternative to filtering, we can use multi-year data to estimate treatment effects using timespans other than fall to spring. For example, with the two-year span data of fall 2012 to spring 2014, we can compare estimates of fall 2012–spring 2013 to fall 2012–fall 2013 or compare fall 2013–spring 2014 to spring 2013–spring 2014. The purpose for this is that the large differences in test duration are generally between fall and spring, with fall durations typically shorter than spring durations. Therefore, using fall-to-fall or spring-to-spring timespans alleviates the issue.

However, there are potential problems with these alternatives. First, they include summer, and researchers have found evidence that students experience test score declines over the summer. If summer declines are an outgrowth of differences in testing conditions and not related to actual learning, then including summer may result in a more accurate measure of learning during the school year because the pretest and post-test are administered under more similar conditions. However, it may be that some of this summer loss is true loss of the achievement that accrued the prior school year, which should be attributed to the schools and their practices, in which case timespans that include summer are more problematic. Moreover, if we believe that the fall or spring test durations are so short or so long as to result in invalid scores, these alternative durations may also suffer from the same problem.

For spring-to-spring, an additional potential complication is that if most of the treatment effect happens in the first year of exposure to the school or to personalized learning, then this will be missed by not starting from a baseline fall score.[7]

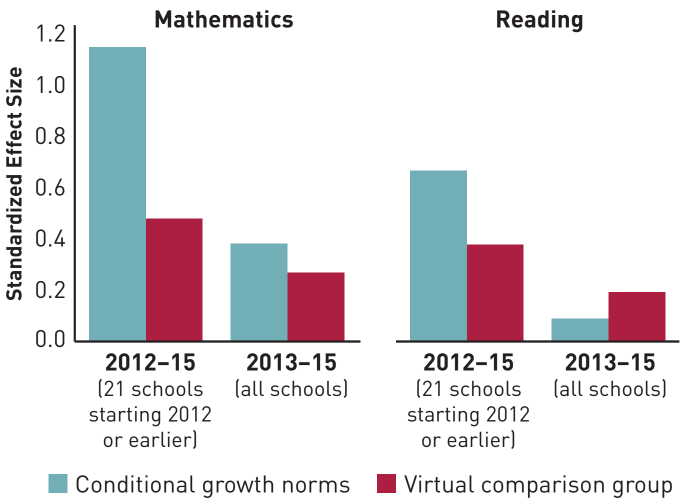
Although these alternate timespans use two-year data to create additional estimates of one-year effects, they differ in important ways from estimates made from one-year span data. In addition to the differences already noted, the data have differences both in the treatment students included (they need to have been present in the personalized learning schools for both years and tested at least three times, as opposed to the one-year span needing the students present just for the two tests in the same year) as well as having a potentially entirely different set of VCGs. For these reasons, we considered the comparison of the different spans to each other, but did not directly compare them to the filtered treatment effect estimates.

A1.6 Results of Sensitivity Analyses

CONDITIONAL GROWTH NORMS

First, we estimated treatment effects using conditional growth norms (CGN), shown in Chart A2. To interpret these results, we focus on the fact that the CGN analysis, like the main analysis, estimates large positive treatment effects. We interpret this as helping to validate the main results. Although the CGN analyses tend to estimate larger treatment effects than the VCG method (with the exception of reading in 2013–15), we focus less on the magnitudes of the estimates because the VCG method is more rigorous in carefully developing a matched comparison group as opposed to benchmarking against national norms as is done in the CGN method.

Chart A2: Contrast of conditional growth norm treatment effect estimates and baseline

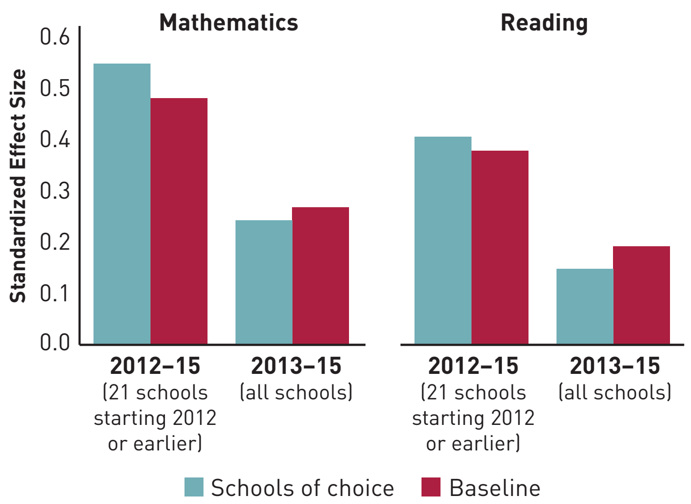


7 Also, on a more technical note for our current data, when we use spring pretests, the students are not matched to their VCGs on this pseudo-baseline. To account for this, we also evaluate a treatment effect where we drop all VCGs not within 3 points on the RIT scale (approximately 95 percent of VCGs are within +/- 3 points of the personalized learning student's score on the interim spring test, while an even higher proportion of VCGs are within +/- 3 points for the true baselines on which they were matched).

SCHOOLS OF CHOICE COMPARISON GROUP

Next, we examined treatment effects using a VCG composed of students only from schools of choice. Chart A3 presents these results. The estimates of the treatment effects are slightly higher for the 2012–15 three-year span and slightly lower for the 2013–15 two-year span, but they are more or less consistent with the main results. We conclude that these results do not cast doubt on the treatment effects estimated by the standard VCGs.

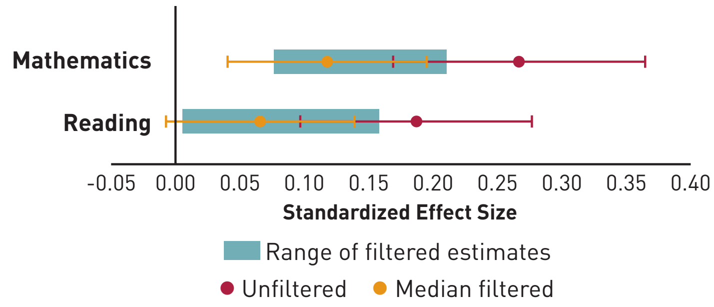
Chart A3: **Schools of choice vs. baseline VCG**



DURATION ANALYSIS

We applied a variety of student-level and school-level filters to remove anomalous test durations from the analysis. Applying the filters at the student and school levels yields a range of estimates. Chart A4 focuses on the main analytic sample and displays the unfiltered estimate and confidence interval in red and the median filtered estimate and its confidence interval in orange. The blue bars show the range of the filtered estimates (but not their confidence intervals). None of the filters result in negative treatment estimates, but for reading, the median filtered estimate is statistically indistinguishable from zero. Mathematics remains statistically significant after filtering when using the confidence interval of the median filtered estimate. The decrease in the treatment effect due to filtering is about 60 percent.

Chart A4: **Duration analysis with filters**

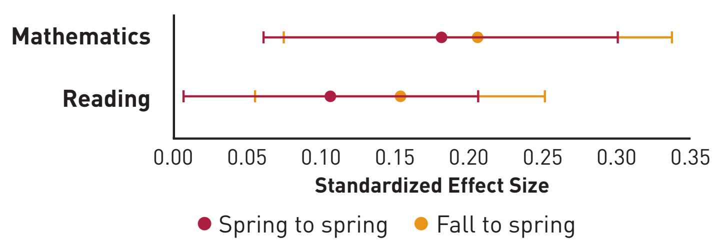


While not presented in detail here, we find that, out of the school-level effect estimates that were positive and significant, just more than 9 percent of the estimates became insignificant (none became significantly negative). Likewise 7 percent of the negative and significant school/subject/span treatment effect estimates became insignificant. Interestingly, 11 percent of school effect estimates that were insignificant became positive and significant with filtering (none became significantly negative).

Finally, we also looked at alternative spans. Given we need an additional year of data to do an alternative span, we cannot investigate the three-year span 2012–15. However, using data from the 21 schools that implemented personalized learning for three years, we can compare the fall 2013 to spring 2015 two-year result (from our main analyses) to estimates that use spring 2013 to spring 2015. Chart A5 presents these results. The spring-to-spring yields slightly smaller treatment effects but not as big of a drop as we observe with filtering. The results are still statistically significant for both subjects.

Chart A5: **Alternative timespans**

Fall 2013 to Spring 2015



APPENDIX 2 Methods for Implementation Analyses

A2.1 Site Visits

Site visit schools were selected based on the fall 2014 administrator interviews and documentation. We purposively selected schools that varied on several dimensions: extent to which the school was implementing competency-based progression, extent to which the school was implementing technology-based personalized learning, grade configuration, and organizational structure (e.g., a school that was part of a charter management organization versus one administered by a traditional district). Teachers were randomly selected for the interviews and focus group so that there was some variation across grade level taught, subject taught, and years of teaching experience. Students were selected for the focus group by a school administrator so that the group would include students with a mix of ages and learning levels, as well as students from both genders.

A2.2 Teacher Logs

Teachers of mathematics and ELA were asked to complete logs, which were brief, online surveys that included questions about daily instructional practice and the factors that influenced their teaching on a particular day. We administered the logs over two 10-day periods in 2014–15, once in the fall and once in the spring, for a total of 20 logs per teacher. In the fall, the logs were distributed to a sample of 257 teachers, and 181 teachers completed at least one log in which they indicated they had provided instruction that day, for a response rate of 70 percent. In the spring, the logs were distributed to a sample of 261 teachers, and 153 teachers completed at least one log in which they indicated they provided instruction that day, for a response rate of 59 percent. The number of logs completed varied by teacher; missing logs were due either to a response of "I did not provide instruction today" or to non-completion. Each day, teachers answered a series of questions while focusing on their interactions with one student during the first 45 minutes of mathematics or ELA instruction. Teachers were asked to focus on a different student for each day that they completed the log. The rationale for asking teachers to focus on a single student rather than the entire class is that the instruction offered, and the nature of the student-teacher interactions, can vary across students. This variability is particularly likely to occur in personalized learning environments.

A2.3 Teacher Surveys

Teachers of mathematics and ELA were asked to provide their perceptions about various aspects of the models, including professional training and support, access to resources, the quality of instructional and curricular materials, use of different models of classroom instruction, use of technology in the classroom, use of data to assess student progress, and obstacles to implementation. The teacher surveys were administered online in the spring of 2015. The survey was distributed to a sample of 261 teachers across the 32 schools in implementation analyses; the response rate was 74 percent. Although most of the survey items were developed specifically for this study, a few were adapted from other RAND surveys or from surveys developed by the University of Chicago Consortium on Chicago School Research (CCSR).

A2.4 Student Surveys

Students were asked to describe their study habits, attitudes toward learning, perceptions about their school, the level of access to technology, and other topics. The student surveys were administered online in the fall and spring of the 2014–15 school years to students in 29 schools with enrolled students who met the age criteria: grades 6 and above or age 11 and older if the school did not use traditional grade levels. The fall survey focused on study habits and attitudes toward learning; the spring survey supplemented these with the remaining topics. Students responded similarly on the items present on both surveys, so this report focuses on the spring results that cover the broader range of topics. We distributed the fall survey to 7,214 students and the spring survey to 7,023 students. Response rates were 74 percent and 77 percent, respectively. As with the teacher surveys, we developed many of the items specifically for this study, but the surveys also included original or modified versions of items from the CCSR's surveys; the High School Survey of Student Engagement, developed by the Center for Evaluation and Education Policy at Indiana University; and the Tripod survey, developed by Harvard University's Ronald Ferguson to measure student opinions of teacher quality.

A2.5 Survey Scales

For the teacher and student surveys, we used exploratory factor analysis to identify groups of survey items that reliably grouped together to address a higher-level construct, and we examined the internal consistency reliability (using coefficient Alpha) of the resulting clusters of items. Based on the results of these analyses, we created multi-item scales by calculating an average item score for each set of items and each respondent. A complete list of the items that comprise each scale, the mean scale score, response scale, and coefficient Alpha are displayed in Appendix 3 (student survey) and Appendix 4 (teacher survey).

A2.6 Analysis of Interview and Focus Group Data

The analysis of the interview and focus group data proceeded in several steps. First, interview notes were compared to the audio recording and cleaned to serve as a near-transcript of the conversation. The cleaned interview notes were then loaded into the qualitative analysis software package NVivo 10 and auto-coded by interview question (i.e., so that responses to specific interview questions were easily accessible) as well as coded using a thematic codebook developed by the evaluation team. Once the thematic coding was complete, we conducted a second round of coding, analyzing the data according to questions of interest (e.g., to what extent are schools implementing competency-based progression?). In this stage, we used an inductive coding process (i.e., codes were derived from the data rather than a structured codebook) to develop responses to the questions of interest.

A2.7 Methods for Analyses Relating Implementation Features and Personalized Learning Effects

Appendix 5 describes the 13 elements of personalized learning that were used in this analysis along with the specific items from administrator interviews, teacher surveys, and student surveys that fed into these variables and decision rules used for coding. To produce final codes for features where we had multiple sources of information, we coded the element as present if all data sources agreed the element was present. Features were scored using all available data sources. Because these variables were coded based on 2014–15 implementation data, we merged them with school-level treatment effect estimates for the same one-year timespan. We then applied qualitative comparative analysis (Ragin, 1987) using the QCA package (Thiem and Dusa, 2013) in the R software in an exploratory fashion, trying different thresholds for defining success until we reached an interpretable parsimonious solution.

APPENDIX 3 Student Survey Scales, Personalized Learning Schools

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
Homework connections (Connectedness, utility and accessibility of out-of-school work)		0.75	3.00
How much do you agree with the following statements about the schoolwork you do outside of your regular school hours? 1 (strongly disagree) to 4 (strongly agree)			
	The schoolwork I do outside of school is connected with what I am learning in school.		
	The schoolwork I do outside of school helps me learn.		
	I am able to access the materials I need to learn effectively outside of school.		

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
The following questions ask about your classroom experiences. When you answer them, please think about your experiences with all of your teachers in math, English/reading, science, and social studies this year, and mark the response that indicates your typical experience.			
Instructional support (Perceptions of how well teachers support student learning)		0.94	3.60
… mark the response that indicates your typical experience. 1 (not at all true) to 5 (very true)			
	My teachers ask questions to be sure students are following along with what we are being taught.		
	My teachers want us to share our thoughts.		
	The feedback that I get on my schoolwork helps me understand how to improve.		
	My teachers accept nothing less than our full effort.		
	My teachers don't let students give up when the work gets hard.		
	My teachers want students to explain our answers—why we think what we think.		
	My teachers check to make sure students understand what we are learning.		
	Students get helpful comments to let us know what we did wrong on assignments.		
	My teachers respect my ideas and suggestions.		
	Students share their ideas with each other about what they are working on during class.		
	In my classes, we learn a lot almost every day.		
	My classmates and I have opportunities to work together and give each other feedback.		
Enjoyment of learning (Extent to which students are engaged in, and enjoy, schoolwork)		0.86	3.30
… mark the response that indicates your typical experience. 1 (not at all true) to 5 (very true)			
	The material I am learning in my classes is interesting.		
	I like the way we learn in my classes.		
	In my classes, learning is enjoyable.		
Student goals and progress (Extent to which students understand goals and track progress toward mastery)		0.84	2.50
… mark the response that indicates your typical experience. 0 (never) to 4 (always)			
	I am required to show that I understand a topic before I move on to a new topic.		
	When I am working on an assignment or activity, I know what the goals of that assignment or activity are.		
	I keep track of my learning progress using technology (for example, using an online gradebook or portfolio).		
	If I have trouble understanding the material when I'm using technology, I am able to get help quickly.		
	I have opportunities to review or practice new material until I really understand it.		
Student choice (Perceptions of the extent to which students are able to make choices about their learning)		0.80	2.10
… mark the response that indicates your typical experience. 0 (never) to 4 (always)			
	I have opportunities to choose what instructional materials (such as books or computer software) I use in class.		
	I have opportunities to choose what topics I focus on in class.		
	I work on different topics or skills than what my classmates are working on at the same time.		
	I am given the chance to work through instructional material at a faster or slower pace than other students in the class.		

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
ELA instruction (Perception of the cognitive complexity of ELA instruction)		0.90	1.60
When the focus of your learning is reading and writing (e.g., in an English class), how often do you do the following? 0 (never) to 3 (almost all the time)			
	I discuss my point of view about something I've read.		
	I discuss connections between what we are reading in class and real-life people or situations.		
	I discuss how culture, time, or place affects an author's writing.		
	I explain how writers use tools like symbolism and metaphor to communicate meaning.		
	I improve a piece of writing as a class or with partners.		
	I debate the meaning of what we are reading in class.		
Mathematics instruction (Perception of the cognitive complexity of mathematics instruction)		0.83	1.30
When the focus of your learning is math, how often do you do the following? 0 (never) to 3 (almost all the time)			
	I write a few sentences to explain how I solved a math problem.		
	I write a math problem for other students to solve.		
	I discuss possible solutions to problems with other students.		
	I use math to solve real-world problems.		
	I solve a problem with multiple steps that take more than 20 minutes.		
School-wide future orientation (Extent to which teachers help students plan for the future)		0.89	3.00
How much do you agree with the following statements about your school? 1 (strongly disagree) to 4 (strongly agree)			
	Teachers make sure that all students are planning for life after graduation.		
	Teachers work hard to make sure that all students are learning.		
	School is seen as preparation for the future.		
	All students are encouraged to go to college.		
	Teachers pay attention to all students, not just the top students.		
	Teachers work hard to make sure that students stay in school		
Student engagement (Extent to which students enjoy and feel comfortable in school)		0.92	2.90
How much do you agree with the following statements about your school? 1 (strongly disagree) to 4 (strongly agree)			
	Overall, I feel good about being in this school.		
	I care about this school.		
	I feel safe in this school.		
	My opinions are respected in this school.		
	There is at least one adult in this school who knows me well.		
	I can be creative in classroom assignments and projects.		
	I am comfortable being myself at this school.		
	I am an important part of my school community.		
	If I could choose a school right now, I would choose this school.		
Tech use (Access to, and support for, technology)		0.77	3.10
How much do you agree with the following statements? 1 (strongly disagree) to 4 (strongly agree)			
	I have access to technology outside of school whenever I need them.		
	If I need help using technology when I'm at **home,** I have someone who can help me.		
	If I need help using technology when I'm at **school,** I have someone who can help me.		
	At my school, we learn how to tell whether or not information on the Internet is trustworthy.		

APPENDIX 4 Teacher Survey Scales, Personalized Learning Schools

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
Professional development (Quality and usefulness of professional development)		0.89	2.90
Please indicate your level of agreement with each of the following statements about all of your professional development experiences during the current school year (2014-2015, including summer 2014). My professional development experiences this year... 1 (strongly disagree) to 4 (strongly agree)			
	Have been well aligned with the Common Core State Standards or other standards that my state or district has adopted.		
	Have been designed to address needs revealed by analysis of student data.		
	Have been useful for improving my instruction.		
	Have helped me understand how to personalize goals for students.		
	Have helped me implement the technology used in my classroom.		
	Have familiarized me with a variety of approaches to instructional delivery.		
	Have addressed ways to collaborate with students and families to develop instructional goals and approaches.		
School professional environment (Staff collegiality and perceptions of administrator support)		0.82	3.30
Rate your level of agreement with each of the following statements about your school. 1 (strongly disagree) to 4 (strongly agree)			
	The teachers at my school collaborate well with one another.		
	The teachers at my school are highly focused on the mission of improving student learning.		
	Administrators at my school are highly supportive of teachers.		
	Administrators at my school are highly focused on student learning.		
	Administrators at my school trust teachers to make decisions about their own instruction.		
Student respect and motivation (Extent to which students are respectful and motivated)		0.87	2.80
Rate your level of agreement with each of the following statements about your school. 1 (strongly disagree) to 4 (strongly agree)			
	Students in this school respect one another.		
	Students in this school respect the school staff.		
	Students in this school are motivated to achieve.		
	Parents and other family members are involved in students' education.		
School data systems (Perceptions of the quality and usefulness of data and data systems)		0.91	3.10
Please indicate your level of agreement with each of the following statements. 0 (N/A) to 4 (strongly agree)			
	I have access to high-quality assessment data that help me adapt the pace or content of instruction to meet students' needs.		
	The data system provides real-time data that is actionable.		
	Our school's data system includes achievement measures that provide information about students of varying achievement levels, including students who are above or below grade level.		
	Our school's data system provides information at a level of detail that helps me inform my instruction (e.g., breakdowns for specific skills or topics).		
	Our school's data system is easy to use.		
	I can use the school's data system to easily produce the views or reports I need.		
Learner profiles (Characteristics of student learner profiles)		0.88	1.80
Do your school's learner profiles or learning plans have these attributes? 0 (not at all) to 3 (a great extent)			
	Exists for every student.		
	Are frequently updated to incorporate new information.		
	Summarize the student's strengths, weaknesses, and progress, drawing on multiple sources of information, including standardized tests and other information.		
	Summarize the student's goals, interests, and aspirations.		
	Set forth a personalized plan for students to accomplish instructional goals.		
	Are routinely accessed/updated by teachers.		
	Are routinely accessed/updated by students.		
	Are routinely accessed/updated by parents or guardians.		

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
Please indicate the extent to which each of the following statements describes your curriculum and instruction. 0 (not at all) to 3 (a great extent)			
Project-based learning (Extent of project-based learning practices)		0.86	1.20
	I assign projects that extend over several weeks or months.		
	I assign projects that are interdisciplinary (e.g., combining science and literature).		
	Students have opportunities to provide input into the design and focus of project work.		
Student awareness of goals and progress (Extent of practices to support goal awareness and progress monitoring)		0.71	2.20
	I clearly present the goal or objective for each assignment.		
	I have devised strategies that allow students to keep track of their own learning progress.		
	When students are working on an assignment or activity, they know what the goals of the assignment or activity are.		
Competency-based learning (Extent of practices to support competency-based learning)		0.80	2.00
	I require students to show that they understand a topic before they can move onto a new topic.		
	Different students work on different topics or skills at the same time.		
	I give students the chance to work through instructional material at a faster or slower pace than other students in this class.		
	Students have opportunities to review or practice new material until they fully understand it.		
Technology for personalization (Use of technology to support personalization)		0.75	2.00
	Students keep track of their own learning progress using technology (for example, by using an online gradebook or portfolio).		
	I am usually accessible to students via electronic communication when I am not available face-to-face.		
	Students are able to access instructional materials both in and outside of the classroom.		
Student choice and engagement (Emphasis on student choice and engagement)		0.75	1.60
	Students have opportunities to choose what instructional materials (such as books or computer software) they use in class.		
	Students have opportunities to choose what topics they focus on in class.		
	I provide a variety of materials or instructional approaches to accommodate individual needs and interests.		
	I connect what students are learning with experiences they have throughout the rest of the school day or outside of school.		
	I frequently adapt course content to meet students' needs by providing additional assignments, resources, and activities for remediation or enrichment.		

Scale Name	Question and Items Included in Scale	Alpha	Scale Mean
Technology curriculum (Access to high-quality technology-based curriculum materials)		0.96	2.90
I have adequate access to **technology-based** *curriculum materials that: 1 (strongly disagree) to 4 (strongly agree)*			
	Are of high quality.		
	Address the learning needs of all of my students.		
	Are easy for me to use in the classroom.		
	Are easy for my students to use.		
	Do not require frequent technical support.		
	Contribute to my efforts to promote college and career readiness.		
	Support anytime/anywhere learning by being accessible at other times and in other places.		
Non-technology curriculum (Access to high-quality non-technology-based curriculum materials)		0.95	2.80
I have adequate access to **non-technology-based** *curriculum materials that: 1 (strongly disagree) to 4 (strongly agree)*			
	Are of high quality.		
	Address the learning needs of all of my students.		
	Contribute to my efforts to promote college and career readiness.		
	Support anytime/anywhere learning by being accessible at other times and in other places.		

APPENDIX 5 Personalized Learning Attributes, Definitions, and Coding

Learner Profiles

PERSONALIZED GOALS FOR STUDENTS: Students have individual goals that are specific to their learning needs rather than goals for a homogenous group of students.

PRINCIPAL INTERVIEW: To what extent is there collaboration among teacher, student, and student's family to develop a personalized learning plan? [If the personalized learning plans include goals developed for individual students, code 1.]

STUDENT SURVEY: My teachers and I work together to set personal goals for my own learning.*

TEACHER SURVEY: Does your school use frequently updated, shared documents, either paper or electronic (such as learner profiles and learning plans), to document each student's strengths, weaknesses, and goals along with individualized plans to accomplish those goals? [If more than half of teachers in a school say yes, code 1.]

STUDENT DATA PROVIDED AND DISCUSSED WITH STUDENTS: The discussion about data includes students and relates to the personal learning goals of the student.

PRINCIPAL INTERVIEW: To what extent are learning goals/personalized learning plans shared and discussed with students? [If the personalized learning goals/plans are shared and discussed with individual students, code 1.]

Personal Learning Path

OUTSIDE OF SCHOOL LEARNING: Opportunities to work on schoolwork (e.g., homework, projects, assessments) outside of instructional hours. Work outside of school hours does not have to be technology-based.

PRINCIPAL INTERVIEW: In general, how much instruction occurs outside of school?**

STUDENT SURVEY: During a typical school week, how many hours do you spend on schoolwork outside of your regular school hours? [Coded 1 if more than half of students report greater than zero.]

FLEXIBLE/MULTIPLE PATHS FOR STUDENTS THROUGH CONTENT: Flexibility for how students move through the content is built into the school model and a variety of instructional formats are used. For example, the school uses a station rotation model or a combination of traditional instruction and digital content or project-based learning. At minimum, flexible approaches are used in mathematics and ELA classes. Use of digital content or materials is not required.

PRINCIPAL INTERVIEW: Can you describe how students are grouped for instruction? What is the rationale for this approach and does it vary for different students or groups of students? Can you describe the most common instructional approaches used in this school? To what extent does use of these approaches vary?***

STUDENT SURVEY: During a single lesson, I have opportunities to learn in different ways, such as listening to the teacher present to the whole class, working in small groups, or working by myself.*

TEACHER SURVEY: I provide a variety of materials or instructional approaches to accommodate individual needs and interests.*

Note:

* Coded 1 if the item mean or scale mean is greater than response scale midpoint.

** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element schoolwide.

*** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element in at least mathematics and ELA classes.

INDIVIDUALIZED STUDENT SUPPORT: There is time during the school day for one-to-one academic support for students tailored to student needs, whether those needs are learning below-grade-level content or working on mastering grade-level content (e.g., one-to-one instruction, pull-out tutoring, office hours).

PRINCIPAL INTERVIEW: Are there opportunities during the school day for individualized support for students? [Code 1 if yes.]

TEACHER SURVEY: What percentage of time are the following modes of instruction employed in your classroom: in-person individual tutoring; live or pre-recorded tutoring via the internet? [For every teacher, calculate the sum of the percentage for these two items and then take the mean of that percentage across all teachers in the school. Code as 1 if that mean is above 25.]

Competency-Based Progression

STUDENTS PROGRESS THROUGH CONTENT BASED ON COMPETENCY: Students only advance through the content when they demonstrate competency in the material and students are allowed to reach competency at their own pace (i.e., there is no minimum pace). More specifically, students could learn different amounts of material in a year depending on their pace. Then, at the start of the next year, the student picks up learning at the appropriate place based on where the student left off the previous year. At minimum, available in mathematics and ELA classes.

PRINCIPAL INTERVIEW: To what extent does this school use a competency-based model in which students advance through content at their own pace? When is credit awarded? Do students need to demonstrate competency in the material in order to get credit? Are all classes competency-based?***

STUDENT SURVEY: Perception of whether instruction is mastery-based (scale)*

TEACHER SURVEY: Competency-based learning scale*

ON-DEMAND ASSESSMENT TO DEMONSTRATE COMPETENCY: "On demand" assessment so that students can demonstrate competency when ready (rather than at the same time as the rest of the class) and then pursue new learning immediately. Assessment may take multiple forms (e.g., quiz, test, project, presentation).

PRINCIPAL INTERVIEW: Can you describe the school's approach to assessment? More specifically, can you describe how often teachers assess student progress, both formatively and summatively, and what types of assessments are used? To what extent can students choose when to take assessments?***

Flexible Learning Environment

STUDENT GROUPING: Student grouping strategies are dynamic, flexible, responsive to student needs and based on data (i.e., not "tracking"). At minimum, available in ELA and mathematics classes.

PRINCIPAL INTERVIEW: Can you describe how students are grouped for instruction? What is the rationale for this approach?***

TEACHER SURVEY: Extent to which teachers use achievement or mastery data to assign or reassign students to groups within classes. [Code each teacher 1 if they mark "moderate" or "large extent." Calculate school mean and code school as 1 if mean >0.5.]

Note:

* Coded 1 if the item mean or scale mean is greater than response scale midpoint.

** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element schoolwide.

*** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element in at least mathematics and ELA classes.

LEARNING SPACE SUPPORTS MODEL: The learning space supports, or does not hinder, implementation of personalized learning.

PRINCIPAL INTERVIEW: Please briefly describe the physical space and how it is organized. Why is the space organized this way? To what extent do you think this organization of the space is effective for personalizing learning and improving student outcomes?**

TEACHER SURVEY: Please indicate whether the following characteristics, or layouts of physical space, exist in your school. For each that does exist in your school, please indicate the extent to which it facilitates or hinders personalized learning. [If a teacher marks anything as a hindrance, code that teacher as "hinder." If more than half of the teachers in a school are coded "hinder," then code school as 0.]

STRUCTURE OF LEARNING TIME: Structure of learning time is responsive to student needs via flexible scheduling or scheduling that is responsive to student needs. At minimum, available in ELA and mathematics classes.

PRINCIPAL INTERVIEW: Please briefly describe the school schedule: How long are instructional periods and does the length vary? To what extent does the schedule vary for individual students or groups of students? How are instructional periods organized in terms of teacher staffing, length of instruction, and student assignment?***

STUDENT SURVEY: Student Choice Scale*

TEACHER SURVEY: Students have opportunities to choose what instructional materials (such as books or computer software) they use in class; Students have opportunities to choose what topics they focus on in class; I provide a variety of materials or instructional approaches to accommodate individual needs and interests. [Calculate mean of the three items for each teacher, average these to get school mean, code school as 1 if mean is above the midpoint of the response scale.]

EXTENDED LEARNING TIME FOR STUDENTS (EXTENDED SCHOOL DAY OR YEAR): School day longer than 6.5 hours of instructional time or school year longer than 180 days of instruction for students. Teacher prep and professional development not included in instructional time.

PRINCIPAL INTERVIEW: How long is the school day for students/teachers? How long is the school year for students/teachers? How much of the teachers' school day is instructional time? [Code 1 if instructional time is greater than 6.5 hours per day or 180 days per year.]

TECHNOLOGY AVAILABLE TO ALL STUDENTS: Technology is a key aspect of the school model and is available to all students in some way. Can include one-to-one student-to-device ratio or opportunities to use technology during the day.

PRINCIPAL INTERVIEW: Does the school have a one-to-one student-to-device (e.g., laptop, tablet) ratio? To what extent does the school rely on technology-based curriculum or assessment materials?**

TEACHER SURVEY: Technology for Personalization Scale*

College and Career Readiness

DEVELOPING COLLEGE/CAREER PREPARATION SKILLS: Curriculum, activities, or programs that are intended to develop students' college/career readiness. Activities or programs can be academic (e.g., college-level courses) or non-academic (e.g., college visits or career surveys).

PRINCIPAL INTERVIEW: How does this school prepare students for life after high school? Are there other learning opportunities/experiences (e.g., courses for college credit, internships, or work experiences) available to students? What supports for college/career counseling are available to students?**

STUDENT SURVEY: Have you ever talked with a counselor or teacher to plan out courses and other educational experiences so you'll be able to meet your goals for life after high school? [Code 1 if >50% of students respond "yes."]

Note:

* Coded 1 if the item mean or scale mean is greater than response scale midpoint.

** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element schoolwide.

*** Coded 1 if the responses to these questions, when taken together and compared with the definition of the variable, indicated that the school was implementing the element in at least mathematics and ELA classes.

Design: KSA-Plus Communications, Inc.

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Funded by

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