**Informed Decision Making
and Higher Academic Achievement**
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Abstract

This study investigated the impact of data-informed decision making on student learning. The study took place in the School District of Philadelphia, where the use of an instructional management system was simultaneously deployed along with district-wide reforms that included a district-wide curriculum for mathematics, reading, and language arts, and six-week cycles of learning that included benchmark assessments in those content areas. The study used latent variable growth modeling to compare learning trajectories of select grades of students in schools where all staff had daily desktop access to student benchmarks administered every six weeks (treatment) to the learning trajectories of a matched set of students in schools where such data was directly accessible only to administrators and not to teachers (control). All schools were engaged in the district wide reform. Results showed significantly steeper learning trajectories over a three-year period in the treatment group in comparison to the control in mathematics and reading, language arts, and mathematics, the areas of focus across the district, but not in science, an area not focused on in the reform until the last year of the study.

School districts across the country are using information technology systems as foundations upon which to build more effective data-driven, decision-making processes. The School District of Philadelphia is no exception. In 2002, the district instituted district-wide school reform intended to stem the rising tide of mediocrity among students as evidenced by low graduation rates, high drop-out rates, low attendance, and high rates of academic underperformances by students. The reform included a district-wide K-8 and 9-12 curriculum, accountability for the academic success of all students, and the introduction of six-week cycles of learning informed by online benchmark assessments. The cycles of learning each began with five weeks of teaching and learning aligned to the new curriculum using approved resources; followed by benchmark testing at the fifth week; and finally, differentiation instruction and remediation the sixth week based on analysis of the test results. An essential component of that implementation was the introduction of an online instructional management system (IMS). The IMS allowed for integration of the district's student information, state tests, local benchmark assessment data, curriculum, educational resources, and standards information. It brought these resources to the desktops of teachers and administrators, and enabled the district to institute online benchmark testing, providing a foundation for informed decision making.

This research study was designed to answer research questions related to the impact of the IMS-enabled school intervention (e.g., standardized curriculum, online benchmark assessments, and real-time, online access to student data) on student achievement. The study was conducted in 2006 by the Metiri Group, the state evaluator for Pennsylvania's Department of Education's federal technology program (NCLB II D). Metiri Group worked with Dr. Richard Brown, from the University of Southern California, to conduct the study. The researchers analyzed the impact of the IMS-enabled intervention on student achievement in 41 schools that implemented the online IMS in 2003/2004 (Cohorts 1 and 2), hereafter referred to as the treatment group. The learning trajectories of a group of students in the treatment schools were compared to those of a matched set of students in 12 schools that did not implement the IMS-enabled intervention at the teacher level (remember all principals did have access) until 2005/2006 (Cohorts 8 and 9). The latter shall be hereafter referred to as the control group. The effectiveness of the IMS-based intervention was gauged by student academic achievement, as measured by TerraNova scores in literacy, mathematics, and science. The scores of students in Cohorts 1 and 2 who were in Grades 3, 4, and 5 in 2002-2003 (treatment group) were tracked over three years. The learning trajectories of the students in the treatment group were significantly steeper from 2002 to 2003, 2003 to 2004, and 2004 to 2005 in all three academic areas than those of the students in the control. Those differences continued at significant levels even into the first year of implementation of the IMS-enabled intervention with Cohorts 8 and 9 (control schools).

AT A GLANCE **School District of Philadelphia**	
Organization	School District of Philadelphia
Challenges	Making informed, data-driven decisions that improve the district's performance; effectively tracking the performance of students who move from one school to another within the district during a typical year.
Solution	SchoolNet Instructional Management System (www.schoolnet.com), which enabled the implementation of a district wide curriculum, high-speed, networking to the desktop, online benchmark testing, and data-driven decision making through desktop access to integrated student data.
Outcomes	Study showed that the learning trajectories (reading, language arts, and mathematics) of students in the IMS-solution schools were significantly steeper than that of students in control schools.

Background Information

The School District of Philadelphia began a systematic school improvement process in 2002. The improvement process was intended to increase the academic achievement of all students through a common, comprehensive, rigorous K-12 curriculum, a focus on academic achievement through six-week cycles of learning, and benchmark testing at the fifth week followed by intensive differentiation and/or remediation during the sixth week. A critical component of the school improvement process was the instructional management system (IMS).

The IMS integrated the district's student information, state tests, local benchmark assessment data, curriculum, educational resources, and standards information. It also served as a portal, bringing curricular, instructional, and assessment information to the desktop, integrated in ways that helped teachers, administrators, students, and their families make sound decisions. The School District of Philadelphia selected SchoolNet as the vendor to achieve the data integration and data-informed decision making required to improve teaching and learning in SDP.

The district began its phased roll out of the SchoolNet IMS-enabled intervention in the fall of 2003 after completing a pilot program. Four schools initially tested the online IMS solution in 2001- 2002 and a broader group of 21 schools piloted the solution in 2002-2003. Following that proof of concept, a competitive bid process was conducted, through which SchoolNet, Inc. was selected as the IMS vendor.

SchoolNet was contracted to provide the online instructional management system, the integration of the data, the porting of the data into the system, the integration of the benchmark testing into the system (online and scannable forms) and the presentation and reporting structure for the schools. A first step was the porting over and integration of student data in the system. In 2003 data for more than 200,000 students went live for principals and administrators to access, analyze, and inform decision making. Beginning in 2003 all schools had access to the off-line reports from the IMS, and all administrators received training in using that data to inform decision making.

Intervention

Beginning in 2003, cohorts of 25 schools were incrementally brought online with full electronic access to the system. Assignment to Cohort 1 was based on 1) fiber upgrade schedules, 2) interest by leadership for early adoption, and 3) equitable geographic representation. Assignment to Cohort 2 was based on the same criteria. Technology was not a deciding factor since hardware upgrades were included in the IMS rollout process. Overall, 10 cohorts would be identified, trained, and begin using the IMS system from 2003 to 2006.

Deploying the solution over several years gave the district time to train teachers and administrators, including some who had never made significant use of computers before. Concurrent with the rollout of Cohorts 1 and 2, between October 2003 and February 2004, over 1500 educators were trained on the IMS-enabled solution. That training included four-person "principal teams," including a school principal, a technology lead, a math coach and literacy coach, from the district's 250-plus schools. Those teams worked with the solution and were able to retrieve reports for their teachers, prior to the teachers receiving access to the system.[i]

Schools were selected for Cohorts 1 and 2 based on the aforementioned criteria and subsequently identified by the researchers in 2004 as “treatment sites.” The Research Office of the District identified 12 schools within the district from Cohorts 8 and 9, in which teachers did not gain access to SchoolNet until year 3. The Research Office determined that the student group within these schools were matched to the students in 41 schools in Cohorts 1 and 2 based on 2004 Terra Nova scores (all tests averaged), poverty index, PSSA reading and math where available, racial composition, student enrollment, and teacher experience, in this order. The matched group in these 12 schools served as the control group for this study.

Professional development immediately followed the deployment of the technological infrastructure and the rollout of the laptops for all teachers in the early cohorts. Beginning in October 2003, representatives from each of the first cohorts of SchoolNet IMS schools participated in professional development on a regular basis. The professional development was delivered at the SDP central training facility with trainers from SchoolNet, SchoolWorks, and the staff of the Educational Technology Group. The workshop content focused on the use of the SchoolNet IMS applications, administering benchmark testing online, use of laptops, accessing curriculum resources and using data to identify areas for enrichment, differentiated instruction, and possible mid-course corrections to the school improvement plan. In addition, principals, administrators, and technology leaders from all of the schools in the District were brought in for training in accessing data tools and benchmark testing. Principals and team members from every school in the district received a minimum of 24 hours of professional development related to the SchoolNet IMS program. Beginning in the spring of 2004, the second cohort of 25 schools began their intensive training on each of the online IMS applications. The SDP employed a "train the trainer" model for this project, thus establishing leaders in these schools who then provided "turn around" training to school staff with the support of the Educational Technology Group staff. The Control Cohorts 8 and 9 received basic training on SchoolNet beginning in 2002 (as did all district personnel). However, only the principals (and not their staffs) had robust access to the Internet, online access to SchoolNet, or intensive training on the online components until the winter of 2006.

Time Line for Intervention

Cohort	Professional Development for Off-line Use of the IMS	Technological Infrastructure Deployment	Online IMS Is Deployed for the Cohort	Professional Development for Online IMS Use Begins
Cohort 1	Beginning in October 2003	2002	2003	Fall 2003
Cohort 2	Beginning in October 2003	2002	2003	Winter 2004
Control Schools (from Cohorts 8 and 9)	Beginning in October 2003	2004	2006	Winter 2006

Note: Cohorts 1 and 2 have a combined 41 schools. The set of 12 control schools are from Cohorts 8 and 9.

SchoolNet Instructional Management System

SchoolNet Inc.'s Learning Management System provides teacher tools to improve student achievement. It is designed to help teachers plan, meet, and track standards mastery at the student, class, and school levels. Teachers can use the SchoolNet system to analyze student performance data including test scores, grades, attendance, and other indicators. This enables teachers to adjust instructional practice to meet varying student needs and search for resources aligned to standards. Finally, with SchoolNet teachers can search for instructional material by subject, grade level, creator, keywords, instructional mode, comprehension level, instructional strategy, and learning style.

The two critical elements that technology brings to this new learning process through the Instructional Management System are:

1. Timely access to student data
2. Integration of student data and instructional resources in one system

Evaluation study question addressed by this study:

In the context of the mandated K-8 curriculum and the six-week cycles of learning that included benchmark testing for reading, language arts, and mathematics:

> Did the district attain significantly different achievement gains over a three-year period (2002-2005) in groups of students that were in grades 5, 6, and 7 in 2004-2005 and attended IMS-enabled schools (treatment group) in comparison to a matched group of students that attended schools where the IMS had not yet been fully implemented at the teacher (control group)?

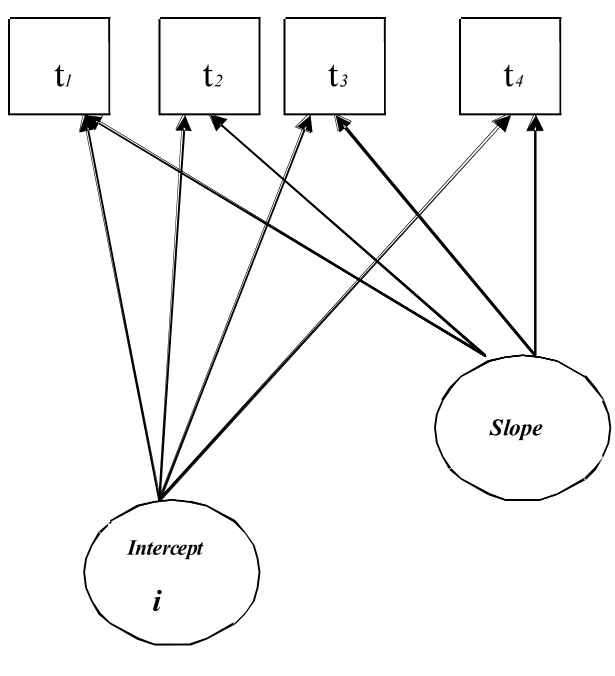
Evaluation Procedures

Data were collected in the schools from two early cohorts (41 schools from Cohorts 1 and 2) and two later cohorts (12 schools from Cohorts 8 and 9). The 12 later schools were matched as controls to the first two Cohorts. Matches were based on 2004 Terra Nova scores (all tests averaged), poverty index, PSSA reading and math where available, racial composition, student enrollment, and teacher experience, in this order. The unit of analysis was the student. The researchers looked at grades 5, 6, and 7 (i.e., students enrolled in those grades in 2004-2005) to ensure availability of sufficient data to estimate a longitudinal growth trajectory.

Analysis Methodology

The methodology presented here is in response to the three questions of interest for this investigation, which can be summed up as, "What is the impact of the technology-enabled intervention on the academic performance of students in the School District of Philadelphia?" In order to identify changes (either positive or negative) in academic achievement, a modeling approach was needed that allowed for the measurement of variables over successive years. Variables that were observable and not observable (latent variables) were examined in a procedure called Latent Variable Growth Modeling (LVGM). By applying a latent variable growth modeling, the researchers could identify the rate of academic progress for groups of students with and without the technology-enabled intervention. Then, these separate growth curves were analyzed for variations across cohorts and subject areas. A graphical depiction of the latent variable growth model used in these analyses can be found in Figure 1 below. Latent variable growth modeling is a method of studying change. Whenever researchers describe change, the form of change must be modeled. This change can be linear or nonlinear (Acock & Fuzhong, 1999). Although higher order or nonlinear models may be applied, in this case the researchers deployed a simple linear model for parsimony and simplicity in describing the relationships. As with any regression model, it is also possible to include any number of potential predictors into the model, such as time varying and time invariant covariates, which may serve to improve the model fit. However, our objective here is not to undertake an exploratory adventure to find the best fitting of all possible models, but rather estimate the parameters of a particular linear model to see if the effects are significant. For all models of change, a starting point must be established, which is called the *intercept (i).* The *intercept (i)* is the beginning value set of data points representing a string of time points. In Figure 1, this is identified as t_1, which represents test scores in the fall of 2002. Indicators t_2 through t_4 depict the data from administration of the Terra Nova during the spring of years 2003 to 2005.

Figure 1 . General latent variable growth model



In addition to the *intercept t(i)*, another latent variable is estimated that represents the rate of change in the outcome variables. This variable is the *slope (s)*. In short, this parameter illustrates how much the curve grows each year (Acock & Fuzhong, 1999). Additionally, latent variable analysis allows for individual differences in development over time because the growth *intercept (i)* and the growth *slope (s)* vary across individuals, resulting in individually varying trajectories for variables over time (Muthen & Khoo, 1998).

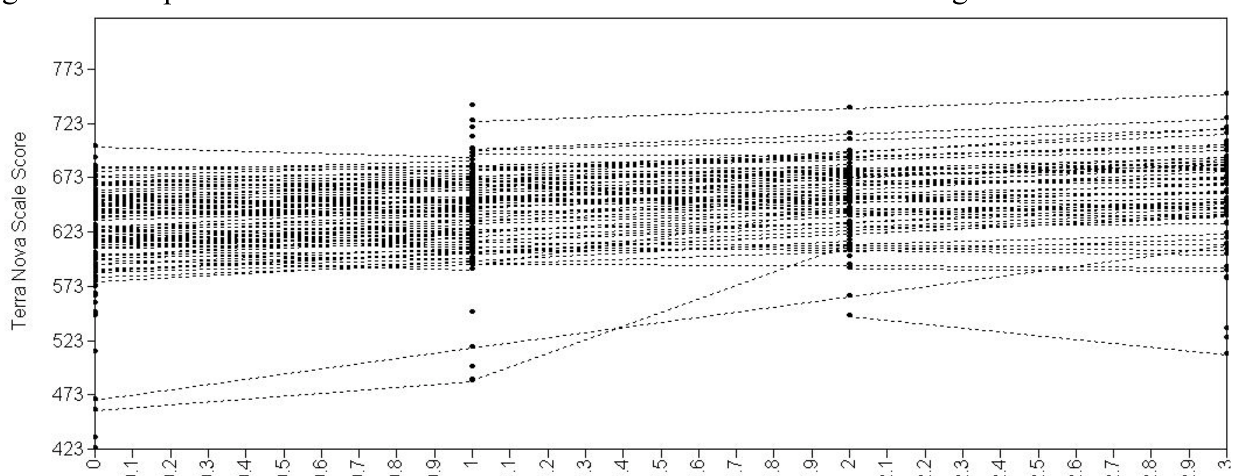
Data Set and Data Elements

Data provided from the School District of Philadelphia included Terra Nova scale score data files in reading, language arts, mathematics, and science for the three-year period of 2002 through 2005. More than 22,000 student records were initially analyzed. Scaled score test data from students initially in grades 3, 4, and 5 in 2002-2003 were matched across years. Additionally, students were identified as being in the treatment condition (Cohorts 1 or 2), or the Control condition (Cohorts 8 or 9). Scale score data are particularly good for this type of analysis for a number of reasons. First, scale scores allow for a common metric across years so longitudinal analyses such as these retain a common metric from one year to the next. Second, since the scale score metrics are not only common across years but also across grades, it is possible to combine students from different grades into a single, more robust, analysis.

Results

As indicated earlier, for each cohort and subject area a growth model was estimated. Then, these growth rates were compared within subject areas across cohorts. Where significant differences existed in rates of change (e.g., slopes), differences in academic progress were identified. For each cohort, an average intercept and slope were estimated, along with the standard errors for each of these estimates. There was much variation in individual students' starting points and rates of change, as can be seen by the example in Figure 2. This figure shows the test scores of a random sample of 200 students in Cohort 1 in reading achievement across the four-year period. Notice the variability in individual rates of progress over time.

Figure 2 . Sample Individual Growth Curves for Cohort 1 Students in Reading



To see how well the proposed models fit the data, a measure of model fit is provided, the root mean square error of approximation (RMSEA). Browne and Cudeck (1993) suggest values ranging from .06 to .10 reflect acceptable to mediocre fit (lower values are indicators of better fit). Values of the RMSEA above .10 indicate relatively poor fit. Thus, for this study, most of the models generated accepted fit with a few exceptions. The Cohort 2 language arts and mathematics models and the Control mathematics model showed fits greater than .10. Caution is urged in interpreting the results from these models.

Results across cohorts in reading are displayed in Table 1. For Cohort 1 students, the intercept was estimated to be 615.82 and the slope was estimated to be 12.14, with a standard error of .2, suggesting that the average rate of growth for these students was a little more than 12 points per year during the period of 2002-2005. The estimated rate of growth for Cohort 2 students during this same time period was 11.19 and for Control students it was 9.35. All three of these estimates are significantly different from one another, indicating that the rate of academic progress in reading for Cohort 1 students was greater than the rate of academic progress in reading for Cohort 2 students or Control students, and that the rate of academic progress in reading for Cohort 2 students was significantly greater than the rate of academic progress in reading for Control students during this period.

Table 1. Parameter Estimates for Reading

	Cohort 1		Cohort 2		Controls	
Intercept	615.82		621.3 2		611.25	
Slope (s.e.)	**12.14**	**(0.2)**	**11.19**	**(0.2)**	**9.3 5**	**(0.2)**
Correlation (s,i)	-0.266		-0.194		-0.197	
RMSEA	0.052		0.068		0.056	

The results for language arts were the same as those for reading. All three groups were significantly different from one another, with the Cohort 1 students showing the greatest rates of improvement (12.2), followed by the Cohort 2 students (11.34) and then the Control students (9.88). Thus, it appears the treatment had a positive effect on the rate of academic progress in language arts as well as in reading.

Table 2 . Parameter Estimates for Language Arts

	Cohort 1		Cohort 2		Controls	
Intercept	614.98		619.92		609.72	
Slope (s.e.)	**12.2**	**0.2**	**11.34**	**0.2**	**9.88**	**0.32**
Correlation (s,i)	-0.057		-0.07		-0.063	
RMSEA	0.086		0.114		0.093	

Similar results were obtained for mathematics, where the slopes in the linear model were estimated to be 20.41, 20.37, and 18.74 for Cohort 1, Cohort 2, and Control respectively (see Table 3). While the slopes for Cohort 1 and Cohort 2 were not statistically different from one another, the slopes for both of the treatment groups were significantly higher than the slope for the Control group, indicating that the rates of academic progress in mathematics for Cohort 1 and Cohort 2 students exceeded the rate of academic progress in mathematics for Control students during this period. Better fitting non-linear models (RMSEAs all .09 or lower) for mathematics yielded virtually the same results.

Table 3. Parameter Estimates for Math

	Cohort 1		Cohort 2		Controls	
Intercept	596.27		600.68		589.61	
Slope (s.e.)	**20.41**	**0.23**	**20.37**	**0.22**	**18.74**	**0.34**
Correlation (s,i)	-0.128		-0.166		-0.069	
RMSEA	0.093		0.134		0.128	

For science, the results were less pronounced (see Table 4). The only statistically significant difference among the slopes was between Cohort 2 and Controls, with the students in Cohort 2 indicating more improvement than did the Control students. There was no statistically significant difference between the Cohort 1 students and the Cohort 2 students, or between the Cohort 1 students and the Control students in terms of their rates of academic progress in science. The standardized curricula for reading and mathematics were deployed in the fall of 2003, along with benchmark assessments for those two content areas. The Science curriculum was not deployed until the following year (2004) and science benchmarks were first administered fall of 2005.

Table 4. Parameter Estimates for Science

	Cohort 1		Cohort 2		Controls	
Intercept	598.98		601.95		592.25	
Slope (s.e.)	**16.99**	**0.22**	**17.82**	**0.21**	**15.98**	**0.32**
Correlation (s,i)	-0.355		-0.53		-0.279	
RMSEA	0.088		0.094		0.091	

Conclusions

From the analyses presented here, we can conclude that students in schools with access to the technology-enabled intervention (the instructional management system, the district-wide curriculum, the online benchmark testing, and school wide access to electronic student data) within the School District of Philadelphia have had significant and positive increases in learning gains in the areas of reading, language arts, and mathematics. Less definitive results were obtained in the area of science. That is, the test scores of students in Cohort 1 schools, where the intervention was in place the longest, increased at a faster pace than did the test scores of students in Cohort 2 schools, where the intervention was not in place for as long a period. In addition, the test scores of students in both the groups of schools using the intervention generally increased at a faster rate than did the test scores of students in the Control schools where the intervention was not in place. This is particularly interesting given that in all subject areas, initial starting levels and rate of growth were negatively correlated, suggesting that having a lower initial scale score value in 2002 relates to greater rates of increase. However, despite the fact that the average starting value for the Control group was, on average, lower than either of the experimental Cohorts, the average growth rates of the two experimental Cohorts were consistently higher than that of the Control group. As noted above, science was not a content topic for the technology/IMS-enabled intervention.

It is important to note that while this study provides evidence of differences in growth rates across the groups, it does not provided detailed information regarding how or why these differences came about. It is possible that the use of the IMS system spurred the differential growth patterns. It is also possible that the professional development that accompanied the introduction of the IMS in the Cohort 1 and Cohort 2 schools contributed to the differences, regardless of teacher use of the IMS. It is even possible that some other unmeasured reform that the researchers are unaware of was simultaneously introduced across the district with particular impact in Cohort 1 and Cohort 2 schools. In regression modeling there is always the possibility that the model may be improved by the inclusion of additional predictors, which when included, change the parameter estimates of the other predictors. Discussions with district personnel in the School District of Philadelphia did not uncover any such reforms that might have had a differential impact across these groups of schools. What we do know is that these groups differ with regard to their inclusion in the technology/IMS-enabled intervention, which included timely access to student data, the integration and delivery of student data, and instructional resources delivered to the teachers desktop. Future research in the district is recommended to better understand any potential confounds to these findings and to better understand just how the IMS is operating to improve student learning.

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[i] Philadelphia Schools Tie Curriculum to Standards, Gain Timely Student Remediation, www.schoolnet.com/success/pdf/Philadelphia.pdf