USEIT

Use,
Support,
and
Effect
of
Instructional
Technology
Study

report fourteen

Examining the Relationship Between Students' Mathematics Test Scores and Computer Use at Home and at School

Report 14

Examining the Relationship Between Students' Mathematics Test Scores and Computer Use at Home and at School

Michael Russell, Laura O'Dwyer, Damian Bebell, & Kevon Tucker-Seeley

Graphic Design: Thomas Hoffmann

Published by inTASC – October 2004

Preferred Citing:

Russell, M., O'Dwyer, L., Bebell, D., & Tucker-Seeley, K. (2004). *Examining the relationship between students' mathematics test scores and computer use at home and at school.* Boston, MA: Technology and Assessment Study Collaborative, Boston College.

Available for download at http://www.intasc.org/studies/USEIT/pdf/USEIT_r14.pdf

Michael K. Russell, Project Director/Boston College

Supported under the Field Initiated Study Grant Program, PR/Award Number R305T010065, as administered by the Office of Educational Research and Improvement, U.S. Department of Education.

USEIT

Use, Support, and Effect of Instructional Technology Study

Use, Support, and Effect of Instructional Technology (USEIT)

Report 14

Examining the Relationship Between Students' Mathematics Test Scores and Computer Use at Home and at School

Introduction

Over the past decade, standardized test results have become the primary tool used to judge the effectiveness of schools and educational programs, and today, standardized testing serves as the keystone for educational policy at the federal level and for many states. During the same time period, substantial investments in educational technology have been made. Since 1996 alone, state and district level agencies have invested over ten billion dollars to acquire and integrate computer-based technologies into American schools. Over this time period, the federal government has spent another three billion dollars on educational technology. As a consequence of these major investments in technology, the average student-to-computer ratio has decreased dramatically over a twenty year period from 125:1 in 1983 to 4:1 in 2001 (Market Data Retrieval, 2003). Given this investment in educational technology coupled with the current focus on standardized tests, it is only natural that educators, policymakers, and the public consider the relationship between expenditures on educational technology and performance on standardized tests.

Since the early 1980s, the positive effects of educational technology have been documented in several hundred formal and informal evaluation and research studies (Sivin-Kachala & Bialo, 1994; Coley, Cradler, & Engel, 1997; Mann, Shakeshaft, Becker, & Kottkamp, 1999). Several studies report that students enjoy classes and learn more in shorter periods of time when computer-based instruction is used (Kulik as cited in Chapman, 2000). Research has also found that when technology is used effectively, students develop stronger critical-thinking and problem-solving skills, and achieve higher-order levels of understanding than in non-technology enriched learning environments (Penuel, Yarnell, & Simkins, 2000). In addition, meta-analyses conducted to examine educational technology-use and achievement issues suggest that specific student uses of technology have positive impacts on student achievement (Kulik, 1994; Goldberg, Russell, & Cook, 2003; Fletcher-Flinn & Gravatt, 1995; Waxman, Lin, & Michko, 2003).

While many studies have examined technology-related issues, observers note that research investigating the effects of educational technology on teaching and learning rarely link these uses to improved standardized test scores (Cuban, 2001; Oppenheimer, 1998). Two such notable studies that attempt to make this link were conducted by Wenglinsky (1998) and Angrist and Lavy (2002).

Wenglinsky (1998) used fourth and eighth grade 1996 National Assessment of Educational Progress (NAEP) data to examine the relationship between technology-use and achievement. Using two measures of technology-use (use of simulation and higher order thinking software, and a measure of more general technology-use) and a nationally representative sample of students, Wenglinsky employed empirical measures of teacher characteristics (including professional development experiences), and aggregated measures of class size and school climate to measure the impacts of technology-use. Matching classrooms on the technology-use measures, Wenglinsky concluded that both fourth and eighth grade students who used simulation and higher order thinking software demonstrated statistically significant higher mathematics scores. However, when considering general student technology-use, Wenglinsky found that computer use was negatively related to mathematics achievement for grades four and eight.

A second large-scale study that examined the relationship between technology-use and academic achievement was conducted by Angrist and Lavy (2002). In their widely disseminated study, Angrist and Lavy use Israeli school data from a 1996 administration of a standardized middle school mathematics and Hebrew test to examine the effects of educational technology on student achievement. In their study, the authors compared levels of academic achievement among students classified as receiving instruction in either high- or low- technology environments. Angrist and Lavy (2002) focused on *access to technology* rather than *actual technology-use* to examine the impacts on achievement. The authors classified schools as "high-access schools" when schools were equipped with computers at a 10:1 ratio, meaning 10 students share 1 computer. Based on this classification system, the authors found weak and, in some cases, negative relationships between technology and student test scores.

While both of these studies attempt to examine the relationship between educational technology and standardized test scores, they are limited by: (1) the way in which students' and teachers' technology-use is measured, and (2) measures of achievement that are not specifically designed to capture the types of improved learning that occurs as a result of technology-use. Specifically, Angrist and Lavy's (2002) study equates access to technology with use of technology. Moreover, the authors equate access at a ratio of 10 students to one computer as a high-use setting. Given that the present student-to-computer ratio in the United States is currently about 4:1, and given the current trend toward 1:1 computing environments (for example, New Hampshire, Vermont, Massachusetts, New York, and Maine each have 1:1 environments available), this study is not very useful for informing technology-related policy and practice decisions in the United States. From a design perspective, it is not surprising that a weak treatment such as having one computer for every ten students would have a negligible impact on student achievement. Moreover, it is important to note that recent research suggests that there are a variety of ways in which students and teachers use technology and these are not equivalent to access (Bebell, Russell, & O'Dwyer, 2004; O'Dwyer, Russell & Bebell, 2004).

Although Wenglinski's analysis of NAEP data does employ two measures of student computer use, teachers' use of computers for instructional purposes is absent from the analyses. In addition, given that NAEP is designed to measure performance trends over time and that the questionnaires are intended to remain relatively stable over time, it can not be expected that the NAEP background questionnaire could be used to capture the rapidly evolving uses of technology. Perhaps more importantly, the test scores used in these analyses provide incomplete information about each student's mathematics achievement. By design, NAEP yields test scores that are representative of a state and of the nation, but not of individuals or of classrooms. For this reason, the use of NAEP test scores to examine the relationship between technology-use and classroom-level performance may be problematic. In fact, Hedges, Konstantopoulis, and Thoreson (2003) have cautioned against placing too much emphasis on Wenglinsky's findings and have argued that the design of the "NAEP data collection process poses problems for drawing inferences about causal relations from its data, and limits the degree of confidence that can be applied to causal conclusions. After considerable investigation and modeling work, we concluded that, given the weaknesses of NAEP data for causal inference, even tentative conclusions about the relation of achievement and computer use on the basis of the NAEP data are not warranted" (p. 38).

Finally, both of these studies rely on either aggregate school level data or individual level data within classrooms and so do not take into account differences within and between classrooms and schools when modeling student outcomes. Given that characteristics of students within a classroom are likely to influence the attitudes and instructional practices of their teachers, and that these practices in turn affect all of the students in the classroom, it is important to examine the classroom as a hierarchical organization within which technology-use occurs. Similarly, since decisions to make technology available in classrooms are typically made at the school or district level, it is important to examine the school system as a hierarchical organization within which technology-use occurs.

Given these methodological and psychometric challenges to estimating the impact of technology-use on student achievement, the study presented here employs multiple measures of how students use technology both at home and at school, examines both total test scores and sub-scale scores on a state test, and employs a multilevel data analysis approach that includes both student- and classroom/teacher-level prediction models to examine the relationship between technology-use and achievement. Specifically, this paper presents a hierarchical regression analysis of the relationship between a variety of student uses of technology, student background characteristics, teacher uses of technology and student performance on the mathematics portion of the grade 4, state mandated paper-based mathematics Massachusetts Comprehensive Assessment System (MCAS) test. Using item level achievement data, individual student's test scores, and student and teacher responses to a survey designed specifically to measure technology use, this study examines the relationship between technology-use and mathematics performance among 986 regular students, from 55 intact fourth grade classrooms in 25 schools across 9 school districts in Massachusetts. Given the widespread and increased interest in both student accountability and educational technology, the study presented here begins to provide insight into how different types of technology-use impact students' mathematics performance. In addition, the findings raise important issues about how technology-use and student learning are measured when attempting to examine the relationship between technology-use and student learning in the area of mathematics. It is important to note that throughout the research presented here, the term technology refers specifically to computer-based technologies and includes personal computers, LCD projectors, and Palm Pilots.

Sample

The research presented in this paper used data collected as part of the Use, Support, and Effect of Instructional Technology (USEIT) Study. The USEIT study was a three-year project that began during the Spring of 2001 and was conducted to better understand how educational technologies are being used by teachers and students, what factors influence these uses, and how these uses affect student learning. During the 2001-2002 school year, information about district technology programs, teacher and student use of technology in and out of the classroom, and factors that are believed to influence these uses were collected through site visits and surveys. In total, survey responses were obtained from 120 district level administrators, 122 principals, 4400 teachers, and 14,200 students from over 200 schools in 22 school districts in Massachusetts. The specific details on the sample, methodologies and analyses of the USEIT data are described in Russell, O'Dwyer, Bebell, and Miranda (2003).

In order to examine the relationship between mathematics achievement and technology-use, we purposively selected approximately fifty grade four classrooms from the original USEIT sample. Specifically, all fourth grade teachers who completed the USEIT teacher survey during the Spring of 2002 were stratified into three groups representing high, medium, and low levels of instructional technology-use. Within each group, a sub-set of teachers were recruited to participate in this study of the relationship between technology-use and achievement. The schools and districts were contacted in the Fall of 2002 and teachers and students were re-surveyed in Spring 2003. Survey responses and achievement data from an additional district in which we were conducting related research were also incorporated into the sample. Thus, the current sample includes a total of 1,213 students and 55 teachers from 25 elementary schools across 9 Massachusetts school districts. The sample of 1,213 students includes students who have been classified as English Language Learners (ELL), students with disabilities (SD), and students who are neither SD or ELL. In order to reduce the possible confounding effects of specialized learning and language needs, this study examined only those students who are classified as non-SD and non-ELL students. Thus, the sample used for the analyses presented here includes 986 regular fourth grade students.

Table 1 displays demographic and aggregate district achievement data for each of the 9 school districts participating in this achievement study.

Table 1: Mean Demographic and Achievement Characteristics for the Participating Districts

	District									Sample versus Massachusetts	
	A	B	C	D	E	F	G	H	I	Sample	MA ('02–'03)
Total # of Elementary Schools	6	3	6	16	6	7	3	3	5	55	1,270
% White	89	86	96	81	85	64	87	81	91	84.3	75.1
% Free Lunch	3	5	6	5	14	24	19	3	2	8.9	26.2
Student : Computer Ratio	4.3:1	5.3:1	4.4:1	7.5:1	6.6:1	10.1:1	4.5:1	N/R	8.4:1	6.4:1	5.1:1
% Classes on Internet	100	100	100	66	100	58	100	N/R	72	86.9	82.8
% Grade 4 Mathematics Advanced	28	30	20	33	15	7	11	35	40	24	12
% Grade 4 Mathematics Proficient	38	35	36	36	32	23	33	32	38	34	28
% Grade 4 Mathematics Needs Improvement	31	29	39	25	41	50	40	25	19	33	43
% Grade 4 Mathematics Warning/Failing	2	5	5	6	12	19	16	7	4	8	16

Source: The district and school summary data has been adapted from the Massachusetts Department of Education Web Site (www.doe.mass.edu).

As reported first in O'Dwyer, Russell, Bebell and Tucker-Seeley (2004), the districts that participated in this study performed slightly higher than the state average on the grade 4 MCAS mathematics test. For example, in this sample 24% of the students scored in the advanced range compared to 12% statewide. Similarly, the average percentage of students classified as white was also slightly higher for the participating districts than the state average, and students in this sample had lower free or reduced priced lunch rates than the state average; 8.9% in the sample compared to 26.2% in the state. In terms of technology access, the district average student-to-computer ratio was slightly higher for the participating districts at 6.4:1 compared to the state average of 5.1:1. From these summary statistics it is reasonable to infer that students in the participating districts were generally more affluent, higher performing in mathematics, and had less access to technology than the average district in Massachusetts.

Instruments

The relationship between use of technology and achievement was examined using data collected through student and teacher surveys and the mathematics portion of the state mandated MCAS test. Each source of data is described separately below.

Technology-Use Surveys

Both teachers and students were administered a survey designed specifically to measure technology use. The student survey included measures of socioeconomic status, students' access to technology in school, the types of technology-use that occur in school across subject areas, personal comfort levels with technology, access to technology at home, and use of technology at home for both academic and recreational purposes. The teacher survey included demographic measures, measures of several types of technology-use in and out of the classroom, teachers' comfort level with technology, and teachers' attitude towards technology. The two survey instruments used in this study were refined and adapted from the original USEIT teacher and student surveys (Russell, O'Dwyer, Bebell, & Miranda, 2003)[1]. Teacher and student survey responses were linked using teacher and student names.

The MCAS Fourth Grade Mathematics Test

The Massachusetts Comprehensive Assessment System (MCAS) is a state-mandated test linked to the Massachusetts curriculum frameworks. Beginning in 1998, the paper and pencil tests were administered in grades 4, 8, and 10 and focused on English/language arts, science/technology, and mathematics. Currently, the MCAS has been expanded across subject areas and grade levels and now includes a third grade reading exam. Like some other state testing programs, MCAS results are used to determine whether an individual student may graduate and for ranking schools and districts.

In the study presented here, students' fourth grade mathematics MCAS scores and mathematics subscale scores from the 2002–2003 MCAS administration were modeled as a function of student and teacher background information and technology-use measures. In all, the total mathematics raw score and raw scores on five MCAS mathematics reporting categories identified by the Massachusetts Department of Education were examined. The outcome variables examined in this research were as follows:

- total math raw score;
- number sense and operations component of the total mathematics score;

- patterns, relationships and algebra component of total mathematics score;
- geometry component of the total mathematics score;
- measurement component of the total mathematics score;
- data analysis, statistics, and probability component of the total mathematics score.

The subscale scores were created by computing the sum of students' scores on each of the sub-domain items. In order to facilitate interpretation of the multilevel regression analysis models, the total raw score and five sub-domain scores were standardized to have a mean of zero and standard deviation of 1. Table 2 contains the reliability for the total MCAS mathematics raw score and for each of the five sub-domain scores (calculated prior to standardization). The Cronbach's alpha for the total mathematics raw score was high at 0.86 but the reliabilities of the sub-domain scores are generally lower, with the reliability for the data analysis, statistics, and probability component of the total mathematics score being the lowest at 0.32. The low reliabilities of the sub-domain measures are likely the result of two conditions: (1) a small number of items measuring each sub-domain, and (2) a lack of unidimensionality. When examined using principal components analysis, only the geometry and measurement sub-domain scales appear to be unidimensional. The magnitudes of the reliabilities have important implications for this research due to the fact that unreliability in the dependent variable is likely to increase the error in the prediction, making it more difficult to isolate statistically significant relationships.

Table 2: Reliability Measures for Achievement Scales

Outcome Measure	Number of Items	Reliability*
Total Mathematics Raw Score	39	0.86
Number sense and operations component of the total mathematics score	15	0.71
Patterns, relationships & Algebra Component of total mathematics score	8	0.49
Geometry component of the total mathematics score	5	0.44
Measurement component of the total mathematics score	4	0.41
Data analysis, statistics, & probability component of the total mathematics score	7	0.32

* Calculated using Cronbach's alpha

Nonetheless, as McNabb, Hawkes, and Rouk state, "[s]tandardized test scores have become the accepted measure with which policymakers and the public gauge the benefits of educational investments" (1999, p. 6). Thus, despite the poor psychometric quality of some the information provided by MCAS, we feel it is important to address the concerns of policymakers and the public by using these measures to examine the relationship between technology-use and MCAS performance. But we also believe it is important to emphasize that the value of such analyses are limited by the technical or psychometric quality of the test scores.

When examining the relationship between student achievement and instructional practices it is important to take into account students' prior achievement. For this reason, student achievement on the third grade 2002 MCAS reading test was included as a control variable when modeling the relationship between fourth grade mathematics achievement and technology-use. At the third grade, MCAS only assesses reading and so a measure of prior mathematics performance was not available. Students' third grade reading scores, fourth grade mathematics scores, and survey responses were combined with their teachers' survey responses allowing the relationship between achievement and technology-use to be examined as function of both student and teacher characteristics while controlling for prior achievement.

Methodology

Over the past two decades, researchers have become increasingly aware of the problems associated with examining educational data using traditional analyses such as ordinary least squares analysis or analysis of variance. Since educational systems are typically organized in a hierarchical fashion, with students nested in classrooms, classrooms nested in schools, and schools nested within districts, a hierarchical or multilevel approach is often required (Robinson, 1950; Cronbach, 1976; Haney, 1980; Burstein, 1980; Bryk & Raudenbush, 1992; Kreft & de Leeuw, 1998). At each level in an educational system's hierarchy, events take place and decisions are made that potentially impede or assist the events that occur at the next level. For example, decisions made at the district level may have profound effects on the technology resources and support available for teaching and learning in the classroom. Similarly, within classrooms, teachers' uses of technology are likely to impact how students use technology during class time.

Given that the characteristics of students within a classroom are likely to influence the attitudes and instructional practices of their teachers and that these practices in turn affect all of the students in the classroom, it is important to examine the classroom as a hierarchical organization within which technology-use occurs. Similarly, since decisions to make technology available in classrooms are typically made at the school or district level, it is important to examine the school system as a hierarchical organization within which technology-use occurs. A hierarchical approach to analyzing the relationship between technology-use and achievement requires the analysis of individuals within classrooms, and has at least three advantages over traditional analyses: (1) the approach allows for the examination of the relationship between technology-use and achievement as a function of classroom, teacher, school, and district characteristics; (2) the approach allows the relationship between technology-use and achievement to vary across schools; and (3) differences among students in a classroom and differences among teachers can be explored at the same time therefore producing a more accurate representation of the ways in which technology-use may be impacting student learning (Bryk & Raudenbush, 1996; Goldstein, 1995; Kreft & de Leeuw, 1998).

The analyses presented in this research were conducted using two-level hierarchical linear regression models. In these models, individual student's MCAS scores were modeled at level-1 as a function of students' school and home technology-uses, socioeconomic status indicators, and grade 3 MCAS performance. These models allowed the total variability in fourth grade MCAS mathematics achievement to be partitioned into its within-classroom and between-classroom variance components, and allowed predictors to be added at each level that explained a proportion of both the within-classroom and between-classroom variance available. Although it may be considered more appropriate to model achievement as varying within-classrooms, between-classrooms within-schools, and between-schools, it was not possible to reliably do so with these data. In order to be able to examine differences between classrooms within schools independently of the differences between schools, more classrooms and schools than are available in this sample would be required. For this reason, the between-classroom variability was confounded with the between-school variability in the models presented in this research.

The general hierarchical model assumes a random sample of i students within j classrooms, such that Y_{ij} is the mathematics outcome variable for student i nested within teacher or classroom j (Bryk & Raudenbush, 1996). Given that intact fourth grade classrooms were sampled, teachers' survey responses were considered analogous to measures of classroom practices and so individual students were considered as being nested within classrooms. The level-1 or student model may be expressed as follows:

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + \beta_{2j} X_{2ij} + \ldots. + \beta_{kj} X_{kij} + r_{ij}$$

In this model, mathematics achievement, Y_{ij} was modeled as a function of a linear combination of student predictors, X_{kij}. This model states that the predicted outcome was composed of a unique intercept β_{0j}, and slope for each classroom β_{kj}, as well as a random student effect, r_{ij}. The intercept represents the base achievement in each classroom and the random student effect was assumed to be normally distributed with a mean of zero and variance, σ^2. The chief difference between this model and an ordinary least squares model is that level-1 predictors may vary across classrooms (Bryk & Raudenbush, 1996). In the models used in this research, only mean achievement was allowed to vary between classrooms.

The variation in the level-1 predictors across classrooms was modeled at the second level; the level-1 predictors were modeled as outcomes at level-2. The level-2 model may be expressed as follows:

$$\beta_{kj} = \gamma_{0k} + \gamma_{1k} W_{1j} + \gamma_{2k} W_{2j} + \ldots + \gamma_{P-1k} W_{P-1j} + u_{kj}$$

Each β_{kj} was modeled as a function of aggregate student characteristics (prior achievement and socioeconomic status indicators) as well as measures of teachers' use of technology and beliefs about technology, W_{pj}. Each γ_{pk} represented the effect of the predictors on the outcome. Each classroom had a unique random effect, u_{kj}, which was assumed to be normally distributed with a mean of zero and variance τ_{kk} for any k.

The standardized total mathematics raw score and five sub-domain measures were modeled as outcome measures (Y_{ij}) in this research. The hierarchical regression analyses were carried out in a number of stages. When conducting any hierarchical analysis, the first step requires the examination of the amount of total variability in the outcome measures that exist within and between classrooms. In order to accomplish this, unconditional models, in which no predictors other than school membership were known, were formulated. To develop a better understanding of the technology-uses that may be associated with mathematics performance, the second stage of the analysis involved theory-driven, exploratory data analysis to identify student and teacher variables observed to be associated with each of the outcome measures. Measures of several different types of technology-use first described in Bebell, Russell & O'Dwyer (2004) were examined during the exploratory data analysis phase.

Guided by past research and theory, and extensive exploratory data analysis, multilevel models were formulated. Using predictor variables identified during the exploratory phase, increasingly complex multilevel models were constructed to predict each of the outcome measures. In total, beginning with a model that included only prior achievement and ending with the most parsimonious model for each outcome, seven models for each outcome measure were formulated. The multilevel models were constructed such that the impact of different categories of predictor variables could be independently assessed. The categories of interest were: prior achievement, socioeconomic status, home technology-use, school technology-use, classroom level measures of student achievement and socioeconomic status, and finally, teacher technology-use. Table 3 contains the student level variables and composite measures used in addition to prior achievement for predicting each of the three outcomes. Principal components analysis was used to confirm the existence of unidimensional student recreational home use and academic home use scales, and to create standardized composite measures of these uses that have a mean of zero and a standard deviation of 1. Reliability coefficients were also calculated. In order to facilitate comparisons among the magnitudes of the multilevel regression coefficients, the student school use measures, the socioeconomic measures, and the measure of prior achievement were also standardized to have a mean of zero and a standard deviation of 1.

Table 3: Student Measures Identified During Exploratory Data Analysis Phase

Measurement Categories	Constituent Items
Student school use of technology (Entered into models individually)	How often do you use a computer in school to work with spreadsheets/databases? How often do you use a computer in school for math? How often does your teacher use a computer for math?
Student recreational home use of technology Cronbach's alpha = 0.74	How often do you use your home computer to play games? How often do you use your home computer to chat/instant message? How often do you use your home computer to email? How often do you use your home computer to search the Internet for fun? How often do you use your home computer to create Mp3/music?
Student academic home use of technology Cronbach's alpha = 0.54	How often do you use your home computer to search the Internet for school? How often do you use your home computer to write papers for school?
Socioeconomic status measures (Entered into models individually)	About how many books of your own do you have at home, not counting school books or comic books? How many computers, if any, do you have at home?

Taking advantage of the power of multilevel models for including group characteristics to predict individual outcomes, measures of teacher characteristics were included to predict student achievement. The teacher variables and composites included in the models are shown in Table 4. As was the case with the student level measures, principal components analysis was used to confirm the existence of unidimensional measurement scales and to create composite measures with a mean of 0 and a standard deviation of 1. The reliabilities of the teacher scales are also included in Table 4.

The reliabilities of the student academic home use of technology composite and the teachers' use of technology for student accommodation composite are quite low at 0.54 and 0.45, respectively and so their regression coefficients will be interpreted in light of this.

Table 4: Teacher Use of Technology Scales and Beliefs About Technology Measure

Measurement Scale	Constituent Items
Teachers' use of technology for delivering instruction	How often do you use a computer to deliver instruction to your class?
Teacher-directed student use of technology during class time Cronbach's alpha = 0.89	During class time how often did students work individually using computers this year? During class time how often did students work in groups using computers this year? During class time how often did students do research using the internet or CD-ROM this year? During class time how often did students use computers to solve problems this year? During class time how often did students present information to the class/ using a computer this year? During class time, how often did students use a computer or portable writing device for writing this year?
Teacher-directed student use of technology to create products Cronbach's alpha = 0.77	How often did you ask students to produce multimedia projects using technology? How often do you ask students to produce reports and term papers using technology? How often did you ask students to produce web pages, Web Sites or other web-based publications using technology? How often did you ask students to produce pictures or artwork using technology? How often did you ask students to produce graphs or charts using technology? How often did you ask students to produce videos or movies using technology?
Teachers' use of technology for class preparation Cronbach's alpha = 0.64	How often did you make handouts for students using a computer? How often did you create a test, quiz or assignment using a computer? How often did you perform research and lesson planning using the internet?
Teachers' use of technology for student accommodation Cronbach's alpha = 0.45	How often do you use a computer to prepare or maintain IEPs using a computer? How often do you use a computer to adapt activities to students' needs?

Results

Figures 1 and 2 display the distribution and mean response for each of the student and teacher survey items examined in this study, respectively. In these figures, the use measures are represented on the original four point scale used on the technology-use survey. Figure 1 shows that students tend to use technology at school less frequently than they use it at home; both recreational and academic technology-uses at home are higher than school uses. At home, students report using their computer to play games more frequently than other uses. The low levels of use of technology in school for math supports previous findings from NAEP secondary data analyses (Hedges, Konstantopoulis, & Thoreson, 2003).

Figure 1: Distribution and Mean Items Responses for Student Uses of Technology

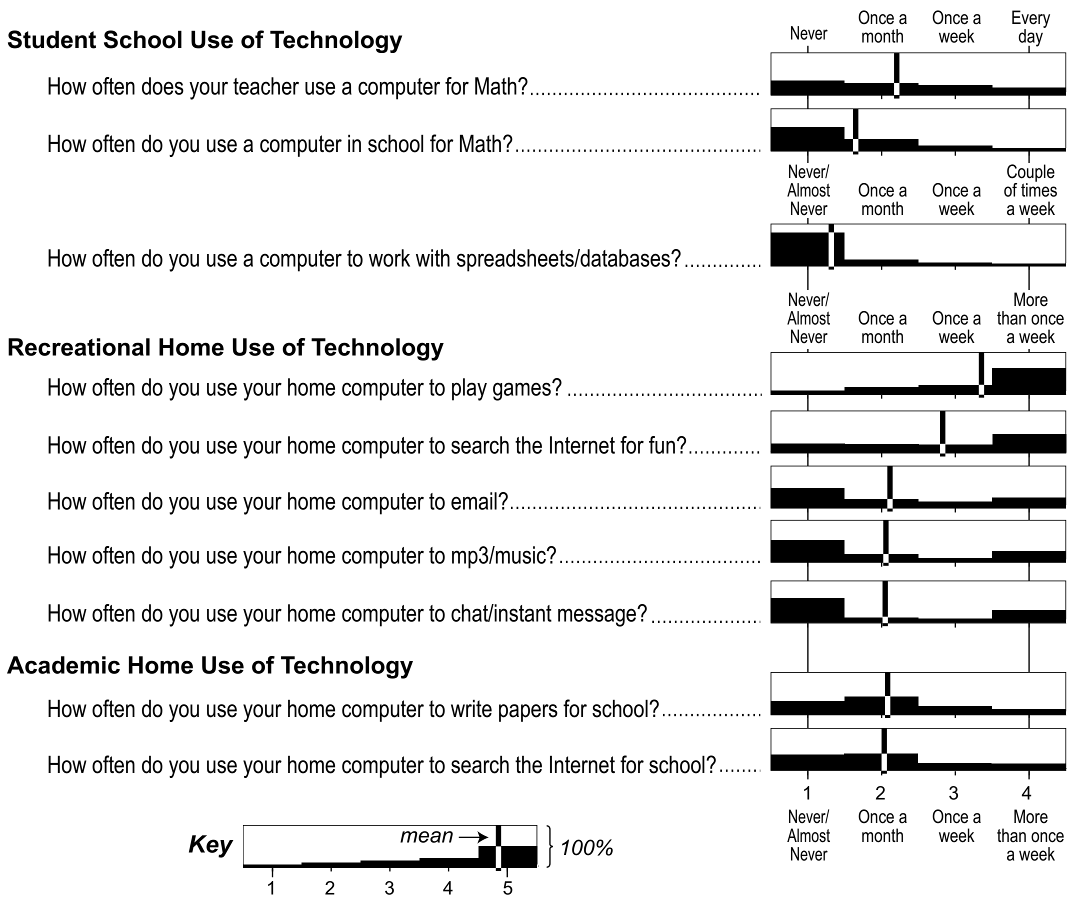

Figure 2 displays similar information for the items used to measure teachers' use of technology. The distributions show that teachers tend to use technology most frequently for preparation purposes outside of the classroom. Teachers also tend to have their students perform tasks using a computer more often than they have them create products using technology. Teachers report that they rarely use technology to deliver instruction in the classroom; on average, teachers only report using technology to deliver instruction several times a year.

(Figure 2 is shown on the following page.)

Figure 2: Distribution and Mean Items Responses for Teacher Uses of Technology

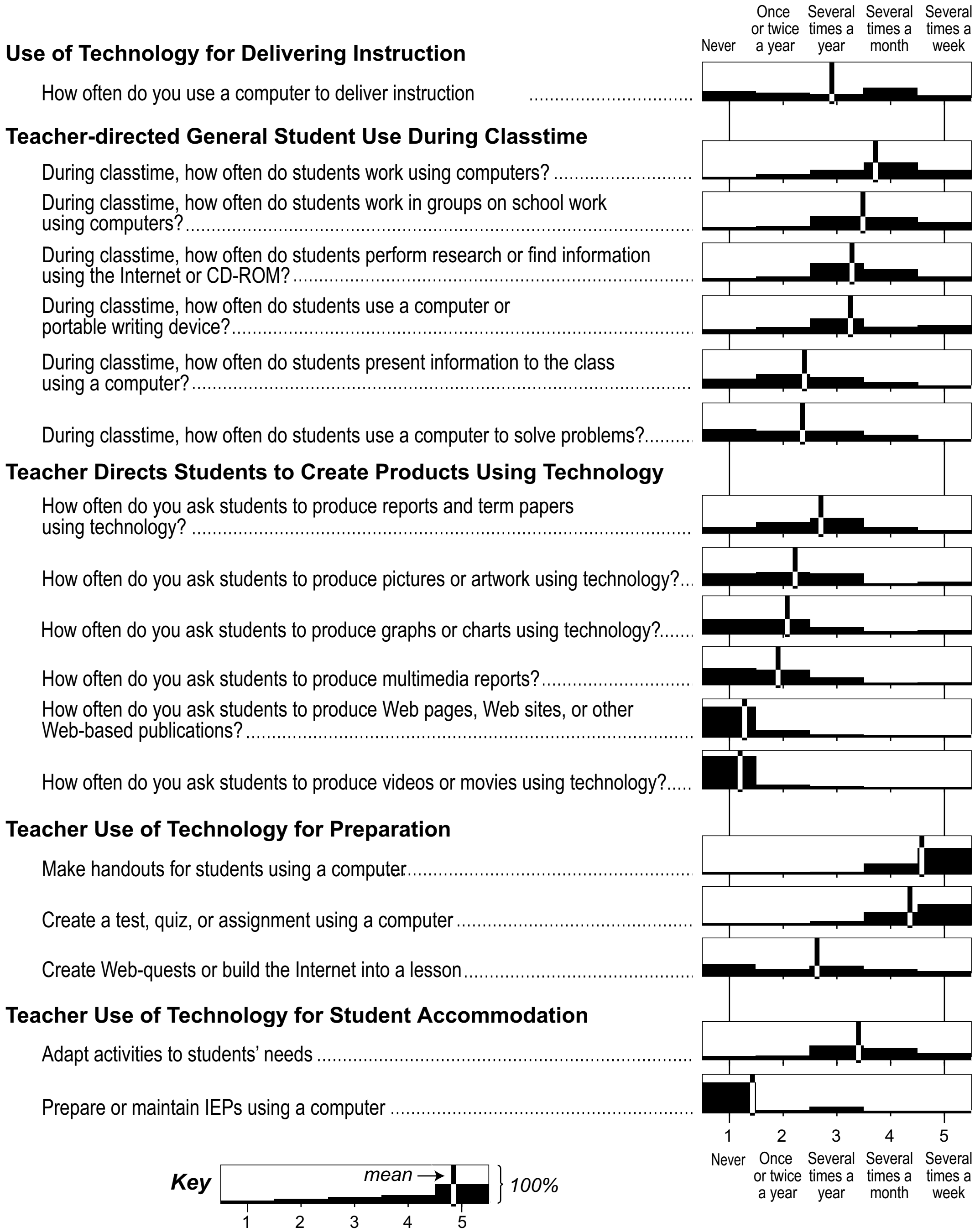

Table 5 presents the variance components for each of the standardized mathematics achievement score measures when the total variability in each was partitioned using the unconditional multilevel models. Although the majority of variability in each measure exists among students within classrooms, a significant proportion of the variability in achievement lies between classrooms for each outcome measure. The largest classroom-to-classroom differences occur for the total mathematics raw score and the number sense and operations component of the total score. For each of these measures, approximately 16% of the total variability in student scores exists between classrooms. The between classroom variance component is smallest for the patterns, relationships, and algebra component and the data analysis, statistics and probability component of the total mathematics score. Although the percentage of variability between classrooms for these two measures is very small, the unconditional models show that the variability between classrooms remains significant. The very small differences between classrooms for these measures will restrict the power of the level-2 models for using classroom level indicators to predict classroom-to-classroom differences.

Table 5: Unconditional Variance Components for the Math MCAS Outcome Measures

	Total Mathematics Raw Score	Number Sense & Operations Component of Math Score	Patterns, Relationships & Algebra Component of Math Score	Geometry Component of Math Score	Measurement Component of Math Score	Data Analysis, Statistics, & Probability component of Math Score
Percent of variance within classrooms	84%	83.4%	95%	86.8%	89.2%	94.0%
Percent of variance between classrooms	16%‡	16.6%‡	5%‡	13.2%‡	10.8%‡	6.0%‡

‡ The percentage of variability between schools is significant for $p < 0.001$.

During the second phase of the hierarchical analysis, characteristics measured at both the student and teacher levels were included in the unconditional models to explain some of the available variance. In all, seven multilevel models were formulated for each of the six dependent variables. The seven models were constructed in such a way as to allow discrete examination of the relationship between each outcome measure and several categories of predictor measures. These categories were: prior achievement, socioeconomic status, home technology-use, school technology use, classroom level measures of student achievement and socioeconomic status, and teacher technology-use measures.

The seven models were constructed in a cumulative manner such that each model included additional categories of predictor measures. The first and simplest model included only third grade achievement to predict the fourth grade outcome measure. The second model included both prior achievement and indicators of socioeconomic status. The third model added students' use of technology at home for both recreational and academic purposes. In addition to the previous variables, the fourth model included measures of students' technology-use at school. The fifth model built upon Model 4 and included measures of student achievement and socioeconomic status aggregated to the classroom level. The sixth model incorporated measures of teachers' use of technology for predicting each of the outcome measures. The seventh and final model was a more parsimonious version of Model 6 in which only predictors that were statistically significant ($p \le 0.05$) are permitted to remain. Tables 6 through 11 present the multilevel regression coefficients and the percent of variance explained by each of the seven models for all six outcome measures. Each model will be discussed in turn.

Total Mathematics Raw Score

Table 6 contains seven multilevel regression models constructed to examine the relationship between student and teacher characteristics and the total fourth grade mathematics raw score. Models 1 through 7 show that prior reading achievement is significantly positively related to fourth grade mathematics performance. The number of computers in a student's home, an indicator of the student's socioeconomic status, is also positively related to mathematics achievement and remains significant in each of the seven models. Students' use of computers at home, for either academic or recreational purposes, though negative is not significantly related to students' total mathematics test scores. In addition, neither the frequency with which students use technology in school to work with spreadsheets/databases nor the frequency with which they or their teacher use computers for mathematics are significantly related to students' total mathematics scores. When classroom and teacher level characteristics are added to the model, classroom-mean prior achievement and the frequency with which teachers direct their students to create products using technology are significantly related to the total mathematics score (Model 6). The regression coefficients in Model 6 suggest that many of the teacher uses of technology included in the model were unable to predict the differences between classroom-mean total mathematics raw scores. Similarly, differences between classroom average raw scores did not appear to be attributable to socioeconomic status differences between classrooms; the classroom aggregate socioeconomic indicators were non-significant at level-2. The negative relationship between the frequency with which teachers directed their students to create products using technology and the total mathematics score became non-significant in the most parsimonious model, Model 7.

The percent of variability in the outcome explained by the models increased as more predictors were added to the models. Prior achievement and socioeconomic status indicators explained 9% of the total variability in the total mathematics score. Including home and school uses of technology in the model (Model 4) increased this amount by only one percentage point to 10%. Given that only predictors measured at the student level were included, Models 1 through 4 were unable to explain any of the variability in achievement among classrooms. It is interesting to note that although only 16% of the total variability in mathematics scores exists between classrooms as evidenced in the unconditional model, Models 5 through 7 explain more than 35% of the available between classroom variance, with Model 7 explaining almost 43% of the available 16%. When considering the power of the model for explaining the total variability in the outcome, including classroom aggregate and teacher measures in the model (Models 5 through 7) increased the percent of total variability explained in the outcome from 10% to 16%.

(Table 6 is shown on the following page.)

Table 6: Total Mathematics Raw Score Model

Outcome = Math Raw Score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							0.03	0.437	0.03	0.437	0.03	0.437		
How often do you use a computer in school for Math?							-0.08	0.096	-0.08	0.096	-0.08	0.096		
How often does your teacher use a computer for Math?							-0.01	0.728	-0.01	0.728	-0.01	0.728		
Recreational Home Use					-0.07	0.076	-0.07	0.079	-0.07	0.079	-0.07	0.079		
Academic Home Use					-0.04	0.430	-0.03	0.497	-0.03	0.497	-0.03	0.497		
About how many books of your own do you have at home, not counting school books or comic books?			0.05	0.128	0.06	0.125	0.05	0.141	0.05	0.141	0.05	0.141		
How many computers, if any, do you have at home?			**0.11**	**0.005**	**0.13**	**0.001**	**0.13**	**0.001**	**0.13**	**0.001**	**0.13**	**0.001**	**0.12**	**0.002**
Grade 3 Reading score	**0.30**	**0.000**	**0.29**	**0.000**	**0.28**	**0.000**	**0.28**	**0.000**	**0.28**	**0.000**	**0.28**	**0.000**	**0.29**	**0.000**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									**0.62**	**0.000**	**0.67**	**0.000**	**0.58**	**0.000**
Teacher-mean number of books in student homes									-0.15	0.426	-0.20	0.230		
Teacher-mean number of computers in student home									0.04	0.779	0.08	0.627		
Teacher-directed student use of technology during classtime											0.08	0.362		
Teachers direct students to create products using technology											**-0.16**	**0.024**	-0.06	0.247
Teachers use technology for preparation											0.03	0.467		
Teachers use technology to maintain IEPs											0.00	0.958		
Teacher use of technology for delivering instruction											0.05	0.382		
Variance Components	**Available Variance**		**Percent Available**											
Between Classrooms	0.15		16%											
Within Classrooms	0.77		84%											
Total Variance Available	0.92		100%											
Residual Variance and Variance Explained	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Classrooms	0.15	0.0%	0.15	0.0%	0.15	0.0%	0.15	0.0%	0.09	39.6%	0.09	37.4%	0.08	42.8%
Within Classrooms	0.70	9.2%	0.69	10.6%	0.68	11.3%	0.68	11.4%	0.68	11.3%	0.68	11.3%	0.69	10.4%
Total Variance Explained		8%		9%		9%		10%		16%		16%		16%

Number Sense and Operations Subtest

Table 7 presents similar models for the number sense and operations component of the mathematics score. As was the case for the total score, prior achievement and the number of computers students report in their homes were positively and significantly related to students' number sense and operations scores. Students' use of technology at home for recreational purposes was significantly negatively related to this measure of achievement, suggesting that students who spend more time using computers at home for recreational purposes were likely to score lower on the number sense and operations component of the test. Models 4 through 6 show that neither the frequency with which students use technology in school to work with spreadsheets/databases or the frequency with which they or their teacher use computers for mathematics are significantly related to this measure students' mathematics ability. The most parsimonious model, Model 7 included only prior achievement, the number of computers students report having in their homes and recreational use of computers at home.

In terms of the explanatory power of the models, prior achievement accounted for a substantial proportion of the total variability explained by the models. In Model 1, prior achievement explained 6% of the total available variance in the number sense and operations component of the total mathematics score. When other predictors were added to the models, the total variance explained increased to a maximum of 14% in Model 7.

(Table 7 is shown on the following page.)

Table 7: Number Sense and Operations Component of the Mathematics Subtest Model

Outcome = Number Sense and Operations Component of Math Score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							0.00	0.955	0.00	0.955	0.00	0.955		
How often do you use a computer in school for Math?							-0.05	0.340	-0.05	0.340	-0.05	0.340		
How often does your teacher use a computer for Math?							0.01	0.733	0.01	0.733	0.01	0.733		
Recreational Home Use					**-0.10**	**0.019**	**-0.10**	**0.020**	**-0.10**	**0.020**	**-0.10**	**0.020**	**-0.11**	**0.005**
Academic Home Use					-0.04	0.425	-0.03	0.466	-0.03	0.466	-0.03	0.466		
About how many books of your own do you have at home, not counting school books or comic books?			0.06	0.069	0.06	0.074	0.06	0.085	0.06	0.085	0.06	0.085		
How many computers, if any, do you have at home?			**0.09**	**0.012**	**0.13**	**0.002**	**0.13**	**0.002**	**0.13**	**0.002**	**0.13**	**0.002**	**0.14**	**0.001**
Grade 3 Reading score	**0.27**	**0.000**	**0.26**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.26**	**0.000**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									**0.58**	**0.001**	**0.60**	**0.001**	**0.53**	**0.000**
Teacher-mean number of books in student homes									-0.22	0.255	-0.26	0.147		
Teacher-mean number of computers in student home									0.13	0.430	0.15	0.424		
Teacher-directed student use of technology during classtime											0.04	0.635		
Teachers direct students to create products using technology											-0.11	0.187		
Teachers use technology for preparation											0.03	0.437		
Teachers use technology to maintain IEPs											-0.02	0.839		
Teacher use of technology for delivering instruction											0.04	0.573		

Variance Components	Available Variance	Percent Available
Between Classrooms	0.16	16.6%
Within Classrooms	0.78	83.4%
Total Variance Available	0.94	100%

Residual Variance and Variance Explained	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Classrooms	0.16	0.0%	0.16	0.0%	0.16	0.0%	0.16	0.0%	0.10	34.0%	0.11	26.4%	0.10	34.9%
Within Classrooms	0.72	7.4%	0.71	8.6%	0.71	9.8%	0.71	9.5%	0.71	9.5%	0.71	9.5%	0.71	9.5%
Total Variance Explained		6%		7%		8%		8%		14%		12%		14%

Patterns, Relationships, and Algebra Subtest

Table 8 presents analyses for the patterns, relationships and algebra component of the mathematics test. In terms of variance structure, the percent of variance between classrooms is substantially smaller for this outcome variable than for the previous two outcomes; 5% for the patterns, relationships and algebra component compared to approximately 16% for both the total raw score and number sense and operations component. The regression coefficients show that third grade achievement is a positive and significant predictor of this mathematics sub-domain score. The number of computers a student reports having in the home is also positively related to this achievement measure and is significant in Models 2 through 7. Unlike the model for the number sense and operations component of the total mathematics score, use of computers at home for recreational purposes is not a significant predictor for this outcome measure. Similar to the previous models, neither the frequency with which students use technology in school to work with spreadsheets/databases or the frequency with which they or their teacher use computers for mathematics are significantly related to students' total mathematics scores. Overall, including only student level predictors in the models explains only about 6% of the total variability among the patterns, relationships and algebra scores.

In terms of the explanatory power of the models, prior achievement accounted for a substantial proportion of the total variability explained by the models. In Model 1, prior achievement explained 5% of the total available variance in the number sense and operations component of the total mathematics score. When other predictors were added to the models, the total variance explained increased to a maximum of 9% in Model 7.

(Table 8 is shown on the following page.)

Table 8: Patterns, Relationships & Algebra Component of the Mathematics Subtest Model

Outcome = Patterns, Relationships & Algebra Component of Math Score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							0.00	0.956	0.00	0.956	0.00	0.956		
How often do you use a computer in school for Math?							-0.03	0.540	-0.03	0.540	-0.03	0.540		
How often does your teacher use a computer for Math?							0.04	0.344	0.04	0.344	0.04	0.344		
Recreational Home Use					-0.06	0.145	-0.06	0.140	-0.06	0.140	-0.06	0.140		
Academic Home Use					-0.05	0.316	-0.05	0.323	-0.05	0.323	-0.05	0.323		
About how many books of your own do you have at home, not counting school books or comic books?			0.03	0.497	0.03	0.450	0.03	0.497	0.03	0.497	0.03	0.497		
How many computers, if any, do you have at home?			0.07	0.071	**0.10**	**0.027**	**0.10**	**0.021**	**0.10**	**0.021**	**0.10**	**0.021**	**0.08**	**0.047**
Grade 3 Reading score	**0.26**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**	**0.25**	**0.000**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									**0.40**	**0.001**	**0.46**	**0.000**	**0.41**	**0.000**
Teacher-mean number of books in student homes									0.06	0.672	-0.03	0.861		
Teacher-mean number of computers in student home									-0.05	0.579	-0.02	0.871		
Teacher-directed student use of technology during classtime											0.09	0.161		
Teachers direct students to create products using technology											**-0.13**	**0.017**	-0.02	0.526
Teachers use technology for preparation											-0.01	0.896		
Teachers use technology to maintain IEPs											-0.01	0.769		
Teacher use of technology for delivering instruction											0.08	0.149		

Variance Components	**Available Variance**	**Percent Available**
Between Classrooms	0.05	5.0%
Within Classrooms	0.91	95.0%
Total Variance Available	0.96	100%

Residual Variance and Variance Explained	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Teachers	0.05	0.0%	0.05	0.0%	0.05	0.0%	0.05	0.0%	0.02	58.5%	0.02	63.1%	0.02	60.8%
Among Students	0.86	5.8%	0.86	6.1%	0.85	6.6%	0.85	6.3%	0.85	6.2%	0.85	6.3%	0.86	6.1%
Total Variance Explained		5%		6%		6%		6%		9%		9%		9%

Geometry Subtest

The models for the geometry component of the total mathematics score are detailed in Table 9. As was the case for the previous three outcome measures, prior achievement was significantly positively related to students' geometry subtest scores. The number of computers a student reports having in the home is also positively and significantly related to achievement in each of the seven models. Student home use of technology for either recreational or academic purposes, though negatively related to achievement, is not a significant predictor of students' geometry scores. The frequency with which students report using computers in school for math is significantly and negatively related to students' geometry scores. Given that prior achievement alone accounts for 5% of the total variability in geometry scores, adding socioeconomic indicators, and computer use at home and at school only improves the predictive power of the model by one percentage point; Models 2 through 4 only explain 6% of the total variability.

Adding class level predictors to the model increases the percent of variance explained to 10%. Classroom-mean prior achievement remains the only significant predictor at the classroom level in Models 5 through 7. Similar to the patterns, relationships and algebra models, the frequency with which teachers direct their students to create products using technology is a significant and negative predictor of the differences among classrooms in Model 6 when included with several other teacher and classrooms predictors, but loses significance in Model 7.

(Table 9 is shown on the following page.)

Table 9: Geometry Component of the Mathematics Subtest Model

Outcome = Geometry component of Math score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							0.05	0.331	0.05	0.331	0.05	0.331		
How often do you use a computer in school for Math?							**-0.09**	**0.037**	**-0.09**	**0.037**	**-0.09**	**0.037**	**-0.09**	**0.021**
How often does your teacher use a computer for Math?							0.00	0.921	0.00	0.921	0.00	0.921		
Recreational Home Use					-0.06	0.131	-0.06	0.134	-0.06	0.134	-0.06	0.134		
Academic Home Use					-0.03	0.421	-0.03	0.457	-0.03	0.457	-0.03	0.457		
About how many books of your own do you have at home, not counting school books or comic books?			0.04	0.252	0.04	0.231	0.04	0.267	0.04	0.267	0.04	0.267		
How many computers, if any, do you have at home?			**0.09**	**0.024**	**0.11**	**0.011**	**0.11**	**0.010**	**0.11**	**0.010**	**0.11**	**0.010**	**0.10**	**0.011**
Grade 3 Reading score	**0.24**	**0.000**	**0.23**	**0.000**	**0.22**	**0.000**	**0.23**	**0.000**	**0.23**	**0.000**	**0.23**	**0.000**	**0.23**	**0.000**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									**0.50**	**0.000**	**0.54**	**0.000**	**0.48**	**0.000**
Teacher-mean number of books in student homes									-0.16	0.289	-0.19	0.163		
Teacher-mean number of computers in student home									0.11	0.430	0.13	0.352		
Teacher-directed student use of technology during classtime											0.15	0.164		
Teachers direct students to create products using technology											**-0.18**	**0.032**	-0.06	0.156
Teachers use technology for preparation											0.01	0.770		
Teachers use technology to maintain IEPs											-0.01	0.855		
Teacher use of technology for delivering instruction											-0.02	0.823		

Variance Components	Available Variance	Percent Available
Between Classrooms	0.12	13.2%
Within Classrooms	0.82	86.8%
Total Variance Available	0.94	100%

Residual Variance and Variance Explained	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Classrooms	0.12	0.0%	0.12	0.0%	0.12	0.0%	0.12	0.0%	0.09	30.8%	0.09	27.1%	0.08	34.4%
Within Classrooms	0.77	5.5%	0.76	6.3%	0.76	6.7%	0.76	6.9%	0.76	6.8%	0.76	6.9%	0.76	6.6%
Total Variance Explained		5%		5%		6%		6%		10%		10%		10%

Measurement Subtest

The two-level regression results for the measurement component of the total mathematics score are contained in Table 10. As was the case for each of the previous models, prior achievement and the number of computers a student reports having in the home are positively and significantly related to students' measurement scores. Neither use of computers at home for academic or recreational purposes, or use of computers at school appears to be significantly related to this measure of achievement. In all, Models 1 through 4 which include only student level measures, explain less than 3% of the variability in the measurement scores that exists within classrooms and therefore, only 2% of the total variance.

At the classroom level, classroom-mean prior achievement and teachers' use of technology for preparation are significantly positively related to this measure of student achievement. Similar to the models for the other outcomes, the frequency with which teachers direct their students to create products using technology is significantly and negatively related to student achievement. In total, the models do not explain a large percentage of the total variability in students' measurement scores; the most that is explained by any of the models is 7% (Model 7).

(Table 10 is shown on the following page.)

Table 10: Measurement Component of the Mathematics Subtest Model

Outcome = Measurement component of Math score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.	Coeff.	Sig.
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							0.07	0.166	0.07	0.166	0.07	0.166		
How often do you use a computer in school for Math?							-0.05	0.406	-0.05	0.406	-0.05	0.406		
How often does your teacher use a computer for Math?							-0.06	0.076	-0.06	0.076	-0.06	0.076		
Recreational Home Use					0.00	0.934	0.01	0.892	0.01	0.892	0.01	0.892		
Academic Home Use					-0.02	0.604	-0.02	0.631	-0.02	0.631	-0.02	0.631		
About how many books of your own do you have at home, not counting school books or comic books?			0.02	0.657	0.02	0.636	0.02	0.641	0.02	0.641	0.02	0.641		
How many computers, if any, do you have at home?			**0.10**	**0.007**	**0.10**	**0.007**	**0.09**	**0.012**	**0.09**	**0.012**	**0.09**	**0.012**	**0.10**	**0.006**
Grade 3 Reading score	**0.14**	**0.002**	**0.14**	**0.003**	**0.14**	**0.003**	**0.14**	**0.003**	**0.14**	**0.003**	**0.14**	**0.003**	**0.14**	**0.002**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									**0.51**	**0.000**	**0.52**	**0.000**	**0.39**	**0.000**
Teacher-mean number of books in student homes									-0.18	0.294	-0.21	0.208		
Teacher-mean number of computers in student home									-0.03	0.851	0.01	0.974		
Teacher-directed student use of technology during classtime											0.03	0.756		
Teachers direct students to create products using technology											**-0.15**	**0.016**	**-0.12**	**0.009**
Teachers use technology for preparation											**0.09**	**0.020**	**0.10**	**0.005**
Teachers use technology to maintain IEPs											-0.02	0.851		
Teacher use of technology for delivering instruction											0.05	0.463		

Variance Components	**Available Variance**	**Percent Available**
Between Classrooms	0.10	10.8%
Within Classrooms	0.84	89.2%
Total Variance Available	0.94	100%

Residual Variance and Variance Explained	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Classrooms	0.10	0.0%	0.10	0.0%	0.10	0.0%	0.10	0.0%	0.07	30.1%	0.06	36.6%	0.06	44.1%
Within Classrooms	0.83	1.9%	0.82	2.6%	0.82	2.4%	0.82	2.5%	0.82	2.4%	0.82	2.5%	0.82	2.6%
Total Variance Explained		2%		2%		2%		2%		5%		6%		7%

Data Analysis, Statistics, and Probability Test

Table 11 presents the results for the data analysis, statistics and probability component of students' total mathematics score. Similar to the previous models, prior achievement is significantly positively related to students' measurement scores. The number of books that students report having in their homes is also significantly positively related to achievement while the frequency with which students report using computers at home for recreational purposes is negatively related to this measure of achievement. When classroom level predictors are added to the model, neither classroom-mean prior achievement, classroom socioeconomic indicators, nor teachers' use of technology are significant predictors of the difference between classrooms in terms of the average data analysis, statistics, and probability scores. Table 11 also shows that these models are not very powerful for predicting the variability in students' data analysis, statistics and probability scores. The most parsimonious model, Model 7, explains only 7% of the total variability in scores.

(Table 11 is shown on the following page.)

Table 11: Data Analysis, Statistics, and Probability Component of the Mathematics Subtest Model

Outcome = Data analysis, Statistics, & Probability component of Math score	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coeff.	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**	**Coeff.**	**Sig.**
Student Level Predictors														
How often do you use computers in school to work with spreadsheets/databases?							-0.05	0.332	-0.05	0.332	-0.05	0.332		
How often do you use a computer in school for Math?							0.07	0.152	0.07	0.152	0.07	0.152		
How often does your teacher use a computer for Math?							0.06	0.140	0.06	0.140	0.06	0.140		
Recreational Home Use					-0.06	0.052	**-0.07**	**0.039**	**-0.07**	**0.039**	**-0.07**	**0.039**	**-0.06**	**0.047**
Academic Home Use					-0.03	0.414	-0.03	0.392	-0.03	0.392	-0.03	0.392		
About how many books of your own do you have at home, not counting school books or comic books?			**0.07**	**0.043**	**0.07**	**0.036**	**0.07**	**0.035**	**0.07**	**0.035**	**0.07**	**0.035**	**0.08**	**0.023**
How many computers, if any, do you have at home?			0.02	0.610	0.04	0.280	0.04	0.212	0.04	0.212	0.04	0.212		
Grade 3 Reading score	**0.23**	**0.000**	**0.22**	**0.000**	**0.22**	**0.000**	**0.22**	**0.000**	**0.22**	**0.000**	**0.22**	**0.000**	**0.22**	**0.000**
Teacher Level Predictors														
Teacher-mean student Grade 3 reading score									0.25	0.057	0.27	0.060		
Teacher-mean number of books in student homes									0.03	0.832	-0.01	0.949		
Teacher-mean number of computers in student home									0.09	0.486	0.09	0.497		
Teacher-directed student use of technology during classtime											0.03	0.752		
Teachers direct students to create products using technology											-0.07	0.347		
Teachers use technology for preparation											0.02	0.644		
Teachers use technology to maintain IEPs											-0.06	0.249		
Teacher use of technology for delivering instruction											0.04	0.577		

Variance Components	**Available Variance**	**Percent Available**
Between Classrooms	0.06	6.0%
Within Classrooms	0.91	94.0%
Total Variance Available	0.97	100%

Residual Variance and Variance Explained	**Model 1**		**Model 2**		**Model 3**		**Model 4**		**Model 5**		**Model 6**		**Model 7**	
	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained	Residual Variance	Variance Explained
Between Classrooms	0.06	0.0%	0.06	0.0%	0.06	0.0%	0.06	0.0%	0.04	29.6%	0.04	22.8%	0.06	0.0%
Within Classrooms	0.86	4.7%	0.86	5.0%	0.86	5.3%	0.86	5.5%	0.86	5.4%	0.86	5.4%	0.86	5.3%
Total Variance Explained		4%		5%		5%		5%		7%		6%		5%

Discussion

To begin examining the relationship between the use of technology to develop students understanding of mathematics and students' mathematics achievement, the study presented here developed several statistical models in which multiple measures of technology-use were used to predict the performance of fourth grade students on the MCAS mathematics test. Recognizing that the MCAS mathematics test assesses several different mathematics sub-domains, the analyses focused both on the effects of multiple uses of technology on students' total test scores as well as their performance within five specific sub-domains. To account for differences in prior achievement and to control for the relationship between socioeconomic status and student performance, the analyses also employed third grade MCAS reading test scores as a covariate and two measures of students' socioeconomic status. Finally, to separate the effects of individual factors and classroom level factors, the analyses employed hierarchical linear regression modeling techniques.

As expected, the analyses of total test scores and each sub-domain score indicate that prior achievement and SES are significant predictors of fourth grade MCAS mathematics scores. This relationship was consistent across all analyses. In addition, with the exception of geometry, all measures of students' use of technology in school included in the analyses did not show a significant (positive or negative) relationship with students' test scores. For geometry, the measure that focused on general use of computers in school for Mathematics showed a small negative relationship with geometry sub-domain scores. Similarly, teachers' use of computers was significantly related with students' performance for only one sub-domain, namely the measurement subtest. More specifically, teachers' use of computers to prepare for instruction had a small positive relationship with students' geometry scores, while teachers directing students to use computers to create products had a small negative relationship with geometry scores. Finally, students' use of computers at home for academic purposes showed no relationship with test performance. However, students' use of computers at home for recreational purposes had a small negative relationship with the number sense and operations, and with the data analysis, statistics, and probability sub-domain scores.

As described above, all of the statistical models accounted for a relatively small percent of the total variance in test scores. Specifically, the largest percentage of total variance explained by the models for the total test score (16%) and the number sense and operations sub-domain scores. Models for the remaining sub-domain scores accounted for 10% or less of the total variance, with the data analysis, statistics, and probability model accounting for the least amount of variance (5%). In part, the low amount of variance accounted for by these models may result from the relatively poor reliability of the sub-domain scores. As shown in Table 2, only the total test score (0.86) and the number sense and operations sub-domain (0.71) scores had reliability indices greater than 0.5. In addition, the use of a covariate that focused on prior reading performance, rather than prior mathematics performance, may have decreased the variance accounted for by prior achievement.

Despite these two shortcomings, perhaps the most noticeable aspect of these analyses is how little variance is accounted for by any individual measure of student or teacher computer use or by the collective set of uses. Although approximately one third of the classrooms that participated in this study were selected because use of technology for instructional purposes was reported to be relatively high compared to all the classrooms that participated in the USEIT Study, this lack of explanatory power may result from the relatively low amounts of computer use for mathematics that occurs even in these "high-use" classrooms. As was shown in Figure 2, a moderate percentage of teachers reported using computers to deliver instruction several times a month or more. However, the survey was not specific as to whether this use occurred during mathematics instruction. In fact, as seen in Figure 1, very few students reported that they or their teachers used computers more than once a month for mathematics and even fewer students reported using spreadsheets of databases once a month or more during the school year. Thus, it appears that, while many teachers regularly use computers to deliver instruction, this use does not typically occur during mathematics instruction. This conclusion is supported, in part, by findings from a separate study that employed the same sample and the same data collection and analytic procedures to examine the relationship between computer uses and MCAS Language Arts scores (O'Dwyer, Russell, Bebell, & Tucker-Seeley, 2004). In that study, the amount of total variance in Language Arts test scores accounted for by the multi-level models ranged from 12 to 25%, with technology-uses related to writing accounting for approximately 2–3% of the variance in MCAS writing scores.

Although this study employed multiple measures of student and teacher technology-use, attempted to control for prior achievement by employing prior year test scores as a covariate, and employed multi-level modeling techniques to account for individual level and classroom level factors that influence test performance, this study could be improved in several ways. First, rather than employing prior year reading scores as a covariate, it would be desirable to include test scores that are more closely aligned with the constructs measured by the current year test(s), namely mathematics.

Second, although multiple measures of teacher and student computer use were employed, many of these measures were still relatively vague. As an example, the most specific student use item asks students how often they use a computer to work with spreadsheets and/or databases. While this item is more specific than asking students how often they use a computer for math (which is another item in the survey), it clusters all potential uses of spreadsheets to explore mathematical concepts into one item. These potential uses may include recording data, creating and working with graphs, creating and exploring algebraic functions, performing basic arithmetic, exploring number patterns, or exploring statistical concepts. While it is unlikely that many of these specific uses are occurring in the classrooms included in this study given the relatively small amount of use for mathematics, in truly high-use settings grouping these multiple and distinct uses into a single measure is likely to obfuscate the effects of technology-use on student learning.

Similarly, unlike Language Arts, which is composed of reading and writing skills and is absent content, mathematics includes a large body of content. As seen in the 4th grade MCAS mathematics test, at least five content areas are expected to be covered during the fourth grade. For each of these content areas, computers may be used in a variety of ways to help students develop their understanding. However, a given use of a computer to develop skill and knowledge in one content area may not be effective for another content area. As an example, building and exploring graphs may be highly effective for geometry and statistics, but not as useful for number sense or basic arithmetic. Thus, when measuring students' use of computers, it may be important to not only develop more precise measures of what students are doing with computers, but also what content students are learning as they use the computers. Although developing such a detailed technology-use instrument would require considerable time and attention and would likely require considerable time for students to complete, doing so would enable richer and more precise estimates of the effects of computer use on students' learning as measured by standardized test scores.

Finally, to better understand the effects of computer use on students' mathematical development, it may be necessary to survey a much larger body of classrooms to identify settings in which high levels of computer use occur. Alternatively, rather than sampling widely and then narrowing on high-use settings, a future study might begin by identifying settings where use is likely to be high and then sample from within those settings to identify classrooms with the highest levels of use. As an example, several districts as well as the state of Maine have developed settings in which each student has their own laptop computer. While access does not equal use, these 1:1 settings may provide fertile ground from which truly high-use classrooms may be identified.

Endnote

1 Original USEiT surveys are available at www.intasc.org.

References

Angrist, J. & Lavy, V. (2002, October). New evidence on classroom computers and pupil learning. *The Economic Journal*, 112, 735–765.

Bebell, D., Russell, M. & O'Dwyer, L.M. (2004). Measuring teachers' technology uses: Why multiple-measures are more revealing. *Journal of Research, Technology and Education*, *37*(1), 45–63.

Bryk, A. S., & Raudenbush, S.W. (1996). *Hierarchical linear models: Applications and data analysis methods.* Newbury Park, CA: Sage

Burstein, L. (1980). The analysis of multi-level data in educational research and evaluation. In D.C. Berliner (Ed.), *Review of research in education* (Vol.8, pp. 158–233). Washington, DC: American Educational Research Association.

Chapman, E. (2000). Alternative approaches to assessing student engagement raters. Practical Assessment, Research & Evaluation, 8(13). Retrieved June 7, 2004 from http://PAREonline.net/getvn.asp?v=8&n=13.

Coley, R., Cradler, J., & Engel, P. K. (1997). *Computers and classrooms: The status of technology in U.S. schools.* Policy information report. Princeton, NJ: Educational Testing Service Policy Information Center. (ERIC Document Reproduction Service No. ED412893)

Cronbach, L.J. (1976). *Research on classrooms and schools: Formulation of questions, design, and analysis* (Occasional paper). Stanford, CA: Stanford Evaluation Consortium, Stanford University.

Cuban, L. (2001). *Oversold and underused.* Cambridge, MA: Harvard University Press.

Fletcher-Flinn, C. M., & Gravatt, B. (1995). The efficacy of computer assisted instruction (CAI): A meta-analysis. *Journal of Educational Computing Research*, *12*(3), 219–242.

Goldberg, A., Russell, M., & Cook, A. (2003). The effect of computers on student writing: A meta-analysis of studies from 1992 to 2002. *Journal of Technology, Learning, and Assessment*, *2* (I). Available from http://www/jtla.org

Goldstein, H. (1995). *Multilevel statistical models.* London: Edward Arnold.

Haney, W. (1980). Units and levels of analysis in large-scale evaluation. *New Directions for Methodology of Social and Behavioral Sciences*, *6*, 1–15.

Hedges, L. V., Konstantopoulis, S., & Thoreson, A. (2003). *Computer Use and Its Relation to Academic Achievement in Mathematics, Reading and Writing. NAEP Validity Studies.* Washington, DC: National Center for Education Statistics (ED).

Kreft, I., & de Leeuw, J. (1998). *Introducing multilevel modeling.* Thousand Oaks, CA: SAGE.

Kulik, J. A. (1994). Meta-analytic studies of findings on computer-based instruction. In E. L. Baker & H. F. O'Neil, Jr. (Eds.), *Technology assessment in education and training* (pp. 9–33). Hillsdale, NJ: Lawrence Erlbaum Associates.

Mann, D., Shakeshaft, C., Becker, J., & Kottkamp, R. (1999). *West Virginia story: Achievement gains from a statewide comprehensive instructional technology program.* Retrieved December 1, 2003, from http://www.mff.org/publications/publications.taf?page=155

Market Data Retrieval. (2003). Technology in education 2003. Shelton, CT: Author.

McNabb, M., Hawkes, M., & Rouk, U. (1999). *Critical issues in evaluating the effectiveness of technology.* Secretary's Conference on Educational Technology: Evaluating the Effectiveness of Technology, Washington, DC. Retrieved November 6, 2003, from http://www.ed.gov/Technology/TechConf/1999.html

O'Dwyer, L.M., Russell, M. & Bebell, D. (2004). *Elementary Teachers' Use of Technology: Characteristics of Teachers, Schools, and Districts Associated With Technology Use.* Technology and Assessment Study Collaborative. Boston College.

O'Dwyer, L. M., Russell, M., Bebell, D., Seeley, K. (2004). *Examining the relationship between home and school computer use and students' English/language arts test scores.* Boston, MA: Technology and Assessment Study Collaborative, Boston College.

O'Dwyer, L. M., Russell, M., & Bebell, D. J. (2004, September 14). Identifying teacher, school and district characteristics associated with elementary teachers use of technology: A multilevel perspective. Education Policy Analysis Archives, 12(48). Retrieved September 14, 2004 from http://epaa.asu.edu/epaa/v12n48/.

Oppenheimer, T. (2003). *The Flickering Mind: The False Promise of Technology in the Classroom and How Learning Can Be Saved.* New York, NY: Random House.

Penuel, B., Yarnall, L., & Simkins, M. (2000, September). *Do technology investments pay off? The evidence is in!* [Electronic version]. Leadership, v30 p.18.

Robinson, W.S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review*, 15, 351–357.

Russell M., O'Dwyer, L.M., Bebell, D., & Miranda, H. (2003). *The USEIT study technical report.* Boston, MA: Technology and Assessment Study Collaborative.

Sivin-Kachala, J., & Bialo, E. R. (1994). *Report on the effectiveness of technology in schools, 1990–1994.* Washington, DC: Software Publishers Association. (ERIC Document Reproduction Service No. ED 371 726)

Waxman, H. C., Lin, M., & Michko, G. M., (2003). *A meta-analysis of the effectiveness of teaching and learning with technology on student outcomes.* Naperville, IL: Learning Point Associates. Retrieved April 22, 2004, from http://www.ncrel.org/tech/effects2/

Wenglinsky, H. (1998). *Does it compute? The relationship between educational technology and student achievement in mathematics.* Princeton, NJ: Educational Testing Service Policy Information Center.

inTASC is a not-for-profit research group that works collaboratively with schools, educational agencies, and businesses to conduct research and development on a variety of issues related to technology and assessment. inTASC brings together researchers who have examined several aspects of technology and assessment in schools over the past decade to focus on new questions and issues that arise from the field. inTASC is unique in that it does not develop research studies and then seek schools to participate in research activities. Instead, schools, educational agencies, and businesses approach inTASC with their own ideas and/or questions that require systematic research to address. Research conducted by inTASC is developed, conducted, and often disseminated in collaboration with our educational and business partners.

inTASC believes that advances in educational technology and continuously emerging applications of those technologies coupled with growing demands to document impacts on teaching and learning requires a dual focus on instructional uses of technology and applications of technology to new forms of assessment. For this reason, inTASC collaborates on research that focuses on instructional uses of technology and on applications of computer-based technologies to the technology of testing and assessment. It is our hope that this dual focus will enable us to provide research-based information to schools and educational leaders about the impacts of educational technology, and to produce new forms of assessment that capitalize on the powers of computer-based technologies and that are more sensitive to the types of learning enabled by educational technologies.

USEIT

Use, Support, and Effect of Instructional Technology Study

www.intasc.org