Does the Presence of School-Sponsored Teacher Technology Training Affect Student Test Scores?

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Abstract

The purpose of this research is to examine the direct effect of school-level teacher technology training on student achievement by using a nationally representative dataset of American high schools. While prior research shows that computer technology alone is not related to improved student outcomes, other studies show that considering contextual variables, like professional development and technology infrastructure, might help explain the effect of digital tools on student test scores. Using a two-level hierarchical linear model, the *ELS:2002* dataset was analyzed to estimate the independent effect of school technology training on the base year of student composite test scores in mathematics and reading. Results show that there is no evidence of an effect of the presence of school-level teacher computer training on student testing outcomes. Implications for school leaders about the quality of technology professional development, along with commentary on assessment in technology-enhanced environments will be discussed.

Comment [AJB1]: Excellent abstract. You present the central purpose, the main problem, what and how you studied it, and the result.

Introduction

The inclusion of technology in schools shows promise to positively influence learning environments. Proponents believe that digital tools could initiate the design of powerful and innovative classroom environments that could give students more complete and authentic learning experiences (Atkins, 2010). In this school of thought, when implemented in the design process and in instruction, the meaningful use of technology could be the gateway to authentic, hands-on learning experiences for students (Bauer & Kenton, 2005; Clarke-Midura & Dede, 2010; Meier, 2005; Roblyer & Doering, 2010). In fact, according to a recent Pew Research Report on teachers' use of technology in the classroom, 73 percent of teachers reported that cell phones and other digital tools have become an essential part of their classroom teaching (Purcell, Heaps, Buchanan, & Friedrich, 2013). Indeed, with the concern about improving student outcomes at the forefront and the growing technological capacities in schools, the integration of digital tools in the classroom has catapulted ahead as a potential tool for reform and school improvement. Yet, if the ultimate measure of success is student achievement scores, there is wavering evidence of technology's effect.

Comment [AJB2]: Good intro of the broader question.

Literature Review

In the past decade, the research base examining the effects of technology integration in the learning environment has been promising, yet still controversial and inconclusive (Lesgold, 2003; Means, Haertel, & Moses, 2003). Some practitioners and scholars have always been skeptical to call the integration of technology in classroom instruction as the panacea for our educational problems (Kimmel & Deek, 1995). For instance, in making their argument for innovating education with technology, Collins and Halverson (2009) cite history as an clear indication of the slow adoption of technological innovation in schools. They note that American schooling is an extremely conservative entity, and it has every right to be because American schools have been successfully schooling the masses in a traditional manner for centuries. To that end, technology presents an inevitable and unwarranted disruption to the status quo, and as with most ambitious educational reforms in the present age, the introduction of technology into instruction is considered to be extremely difficult to catalyze and to manage (Christensen, Horn, & Johnson, 2008; Coburn, Russell, Kaufman, & Stein, 2012). This fact is supported by the lack of empirical evidence that technology itself impacts student test scores.

Comment [AJB3]: Nice compare and contrast. The idea of tech use in schools is not all rosey.

The fact that technology tools and integration have been slow processes could be the result of recent research that shows that it is doubtful that in-school technology use alone has a direct effect on student achievement (Bowers & Berland, 2013; Gulek & Demirtas, 2005; Krentler & Willis-Flurry, 2005; Lemke, Coughlin, & Reifsneider, 2009; Wenglinsky, 1998). Still, other contextual factors, such as technical infrastructure and procurement (Maas & Lake, 2015), implementation fidelity (Shapley, Sheehan, Maloney, & Caranikas-Walker, 2010), professional development (Lawless & Pellegrino, 2007), socioeconomic equity (Warschauer & Matuchniak, 2010), teacher attitudes and beliefs (Ertmer, 2005), and organizational culture (Ademy & Heineche, 2005), might have an additional effect on student-level outcomes where technology is institutionalized.

Thus, because there is little evidence of a direct effect between computers and learning, mediated, multilevel models could help explain the effects of educational technology. Lesgold (2003) outlines a theoretical argument for contextual variables that might be appropriate in measuring student outcomes in innovative environments. As a more qualitative example stemming from Carnegie Mellon's Capability Maturity Model© approach for assessing software

Comment [AJB4]: Nice way to foreshadow the point of the present study.

development (CMMI, 2002), a maturity model for education considers how contextual variables are associated with outcomes. The maturity model is explained in further detail:

> Maturity is defined as involving a set of features…A set of levels or stages is defined, with the assumption that organizations characteristically evolve through these stages in order. […] For each level…a scoring rubric is established that allows raters to reliably score what level the organization has attained on that feature…It can be applied relatively cheaply [and] relevant stakeholder communities can participate directly in discussions of the appropriate features to be included in the model. (Lesgold, 2003, pp. 43-44)

Furthermore, Lesgold (2003) argues that four types of maturity models can be used to assess the effect of digital tools in the classroom, namely instructional, people, infrastructure, and product maturities (p. 47-49). Overall, Lesgold (2003) believes that evaluators can use these different maturity models to qualitatively measure what technology-focused, school-level factors mediate student outcome growth.

However, he also adds that there should be a more "theory-driven causal model [to] look at processes of learning and at what causes learning to take place" (Lesgold, 2003, p. 52). The theory-driven causal model suggests two sets of learning processes: the teacher at the school level and the student at the individual level. In this model, Lesgold (2003) theorizes that school-adopted technology urges teachers to think differently which leads to different classroom behaviors. Consequently, new teaching approaches could possibly change the way students think and perform in class. As seen in Figure 1, the combination of the theory-driven causal model and the four maturity models mentioned earlier, provides the best conceptual framework for subsequent studies in dissecting the effect of educational technology on student outcomes. While the model is somewhat incomplete and simplistic, it does give practitioners and scholars a starting point for examining how the contexts of educational technology are related to one another.

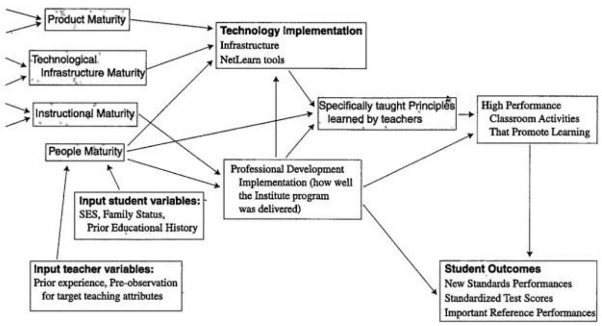

Figure 1. Lesgold (2003) Theory-Driven Causal Model with added Maturity Models for Evaluating Educational Technology in Schools

One important variable at the center of the model above, professional development, has been a topic of interest for decades, and there has been a wealth of literature whose aim is to unpack how professional development is conceptualized, developed, and evaluated (Guskey, 2001). In terms of the field of educational technology, research on technology-focused professional development has started to emerge in the last few years, and most of these studies emphasize long-term, school-situated professional development where teachers have the time and space to collectively build a learning community and truly consider how technology impacts their classroom and their school (Cochran-Smith & Lytle, 2009; Ertmer & Ottenbriet-Leftwich, 2010; Hartnell-Young, 2006; Lawless & Pellegrino, 2007; Meier, 2005; Penuel, Fishman, Yamaguchi, & Gallagher, 2007; Putnam & Borko, 2000). In examining the Lesgold (2003) framework, he theorizes that improved student outcomes are directly related to the presence and implementation of teacher technology professional development and training. On the ground level, some practitioners provide many success stories of technology professional development and its impact on their students; however, in nationally generalizable manner, little is known about if the presence of technology professional development for teachers itself directly affects student achievement in classrooms.

Given this background, the purpose of the present study is to explore how school-level variables, related to technology integration in schools, directly affect student test scores. Although it has already been established that computer use alone does not have a direct correlation to achievement, the study seeks to explore the assumption that professional development can affect student outcomes. In past studies, critics of educational technology research cite a lack of generalizablity and appropriate distribution of sample size (Baker & Herman, 2003). Therefore, a nationally representative dataset, the Education Longitudinal Study of 2002, will be used. Using a two-level hierarchical linear model, the research question for the study is: *To what extent does the presence of school-level technology integration training for teachers affect student achievement, controlling for student SES, school type, urbanicity, and school technology infrastructure*?

Methods

Sample

The raw data from the base year of the Education Longitudinal Study of 2002 (*ELS:2002*) was used as the primary subject of analysis. Originally conducted in the spring of 2002, *ELS:2002* was the fourth iteration of a series of longitudinal studies conducted by the National Center for Education Statistics (NCES) and had a nationally representative sample size of 16,197 high school sophomores in 752 public, Catholic, and private schools across the United States (Ingles et al., 2004). With an emphasis of gathering information on multiple levels, the first round of data collection focused on student achievement scores and high school completion

Comment [AJB5]: A good theory and research based lead into to your framework and research questions.

Comment [AJB6]: Better would be to talk about an association or relationship.

Comment [AJB7]: Good citation to the database manual as well as giving an overview of the data.

rates, as well as student perceptions of building procedures, academic curriculum, school safety, and overall learning environment (Ingles et al., 2004). For the purpose of this study, data analysis only focused on data collected during the base year in order to succinctly explain effect size in one year of data. In addition, because of the ubiquitous nature of the selected variables in schools (i.e., computers and standardized testing), the full sample size of students (*n* = 15,362) and schools (*n* = 752) was considered for use in the study. After listwise deletion, a total of *n*=10,301 students was included in the sample.

Comment [AJB8]: Good. Well stated overall.

However, how many schools were included? That needs to be stated as well.

Usually, many of the variables in a dataset like ELS are measured only in public schools, so all of the private end up getting deleted listwise. If that's true (and it looks like it from your 10k student sample size number) you should note that this study focuses only on public schools with full data.

Individual and School Variable Selection

The individual-level and school-level variables were selected from the *ELS:2002* database to reflect prior literature on the impact of technology-related professional development on student achievement (Brinkerhoff, 2006; Guskey, 2001; Lawless & Pellegrino, 2007; Yoon, Duncan, Lee, Scarloss, & Shapley, 2007). The dependent variable for all models is grade 10 standardized mathematics and reading test scores. The independent variable, teacher training on integrating computers, was selected from the school level data and was a yes or no answer.

The Lesgold (2003) theory-driven causal framework (see Figure 1) guided the inclusion of control variables in the subsequent analytic models. The one student-level control was *socioeconomic status* due to literature finds that SES has a significant effect on test scores (Archibald, 2006). In a similar manner, school-level control variables included *school type* (private/Catholic as the reference category), *urban and suburban* (rural as the reference category), and *technology infrastructure*. *School type* and *technology infrastructure*, as listed in the *ELS:2002* codebook, are dichotomous variables and have been included based on the Lesgold (2003) framework. Particularly for the *technology infrastructure* variable, only computers in the classroom (rather than in libraries or community labs) are used because of the nested nature of the analysis (students in schools). Also, the school ID variable (*F1SCH_ID*) was renamed for data merging. Table 1 outlines each the mean, standard deviation, minimum, and maximum values for each variable (after listwise deletion), along with variable codes.

Comment [AJB9]: Very clear.

Table 1

Descriptives, ELS:2002 labels, and coding for variables included in the model

Variable	Min	Max	Mean	SD	ELS:2002 Variable Label / Name
Student level					
Case ID	3820	16164	9935.218	3620.979	CASE_ID
Student ID	101101	461231	278806.28	107644.697	STU_ID
Grade 10 standardized mathematics and reading test score*	20.91	81.04	52.1269	9.680	BYTXSTD (dependent variable)
Socioeconomic status (SES)*	-2.11	1.98	0.122	0.7469	BYSES2
School Level					
School ID	1011	4612	2787.92	1076.449	F1SCH_ID (SCH_ID)
Public	0	1	0.760	0.427	BYSCTRL = 1; coded as 0 or 1 with Catholic/private as reference category
Urban	0	1	0.305	0.460	BYURBAN = 1, coded as 0 or 1 with rural as reference category
Suburban	0	1	0.497	0.500	BYURBAN = 2, coded as 0 or 1 with rural as reference category
Computers in classrooms	0	1	0.958	0.200	BYA44C, 0 = No, 1 = Yes
Teacher training on integrating computer into class	0	1	0.881	0.324	BYA43D; 0 = No, 1 = Yes
N	10,301				

*This variable was grand-mean centered for analysis and labeled in subsequent reports as *gm_(variablename)*.

Comment [AJB10]: I like that you're following the directions to list all variables in the descriptives. It's my mistake though to have not said though that you don't need to list the ID variables here. Otherwise, this is a great table.

Comment [AJB11]: So this is the composite score variable? If so, you should state that.

Comment [AJB12]: As this is the variable that you're really interested in, it would have been good to give a section or a set of sentences talking through exactly how the question was worded on the survey to provide a bit more information as to what this really represents to the teachers.

Comment [AJB13]: Good APA format. 3 digits after the decimal, clear categories, min max mean and SD. Good note here too.

Pre-Analysis Data Screening

All statistical procedures were conducted in SPSS 22. With multilevel data in national databases, it is important to ensure that data is present on both the individual and school levels and that missing data is handled properly (Raudenbush & Bryk, 2002; Strayhorn, 2009). Therefore, in the initial stages of variable selection, data were copied into two separate files, one for the individual and school levels. ELS:2002 indicates values for missing or incomplete data in the dataset codebook, and for each data file in SPSS, the missing code values were entered into the missing data column for each variable. The student-level school ID variable was renamed, then the two files were sorted by the school ID variable and merged into one multilevel file for further analysis (Heck, Thomas, & Tabata, 2014).

Comment [AJB14]: Good. This entire section has a good flow and provides a clearly stated set of procedures that you used for this analysis, that would allow anyone else skilled in the art of HLM to replicate this study. Excellent.

After running descriptives on the data, the sample size was finalized. For all statistical tests, listwise deletion, the default in SPSS, was utilized to omit missing data. The final sample size used in the data analysis included n=10,301 students. Further discussion on the percentage of missing data will be discussed in the limitations section.

Variables included in the final model were analyzed to verify outliers and the statistical assumptions of normality, linearity, and homoscedasticity (Mertler & Vannatta, 2013). Frequencies did not show a severe split between groups. When testing the assumptions, dichotomous variables remained the same, and all continuous, individual variables appear to be normally distributed. After an initial forward stepwise linear regression, the assumptions of multivariate normality, linearity, and homoscedasticity were confirmed. In addition, a correlation matrix was generated and confirmed no problems with variable correlation. Collinearity diagnostics were also conducted and confirmed that there were no problems with multicollinearity among the variables. Appendix A contains histograms and SPSS output verifying the presence of these assumptions in the data.

Comment [AJB15]: Well put.

In multilevel analysis, the intercept should be interpreted as the expected value when all independent variables are zero. Therefore, continuous variables should be grand mean centered prior to analysis to assist with the intercept's interpretation – the expected value of the dependent variable when all independent variables have their mean value (Heck, Thomas, & Tabata, 2014; Hox, 2002). For the subsequent models, the continuous variables, *grade 10 composite mathematics and reading score* (*BYTXSTD*) and *socioeconomic status* (*BYSES2*), have been grand mean centered.

Comment [AJB16]: Nice.

Analytic Models

As stated earlier, fixed-effect hierarchical linear models (HLM) predicts school-level effects on student-level outcomes; therefore, HLM was used to estimate the independent effect of school-provided teacher technology training on student achievement (Heck, Thomas, & Tabata, 2014; Raudenbush & Bryk, 2002). In general, the equations for the model can be expressed as:

1. Null model (intercept only): $gm\_BYTXSTD_{ij} = \gamma_{00} + u_{0j} + \varepsilon_{ij*}$
2. Level 1: $gm\_BYTXSTD_{ij} = \gamma_{00} + u_{0j} + \gamma_{10} gm\_BYSES2\mathrm{ij} + \varepsilon_{ij*}$
3. Level 2: $gm\_BYTXSTD_{ij} = \gamma_{00} + \gamma_{01} public_j + \gamma_{02} urban_j + \gamma_{03} suburban_j + \gamma_{04} BYA44C_j + \gamma_{05} BYA43D_j + \gamma_{10} gm\_BYSES2_{ij} + u_{0j} + \varepsilon_{ij*}$

Comment [AJB17]: So everything is grand mean centered? Usually in HLM the outcome (dependent) variable is not grand mean centered, as we want the outcome to be fairly "pure" so that we can interpret it. It's necessarily wrong, but it just makes it harder to say specific things about the outcome. However, it does allow you to focus on all of the averages.

If you want to do this, it'd be better to z-score the outcome variable, that way you're able to talk in standard devations.

Comment [AJB18]: Please provide definitions below in regular English as to what each of these mean. Please see examples from the articles read for class on this.

Comment [AJB19]: Oooh, I see what you're doing here. This is confusing as written because of the use of level 1 and level 2. So, here you actually mean that these are your forward stepwise blocks. But I started off by reading these as levels in the analysis. But you provided the full algebraic equations, rather than split them out by level 1 and level 2 as discussed by Heck's readings as well as Bowers.

Ok. These equations look right, although you do need to explain what each piece of them refers to, but I'd change these equation labels. Maybe say Model A, Model B, Model C to avoid confusion.

Results

The purpose of this study is to examine the direct effect of school-level teacher technology training on student achievement by using a two-level hierarchical linear model (HLM). First, in order to decompose the amount of variance on the school and student levels, as well as in the outcome variable, an unconditional model, with no covariates at level one or level two, was estimated (Heck, Thomas, & Tabata, 2014; Hox, 2002; Raudenbush & Bryk, 2002). Table 2 reports the estimates of the fixed effects in the unconditional or null model. Results indicate that the intercept, or the grand mean of mathematics and reading scores for the 10,301 students, is estimated at 51.576 (or 0.551 below the grand mean of 52.167). Likewise, using Table 3, the interclass correlation coefficient (ICC), or the proportion of variance that lies between schools, can be calculated at 0.243 or 24.3%. As a result, because the intercept varies across schools and is significant (Wald Z = 75.412, $p < .001$), and the ICC shows that 24.3% of the variance in test scores lies between schools, continuing to use a multilevel model to explain the variance between and within schools is appropriate (Heck, Thomas, & Tabata, 2014).

Table 2

*Estimates of Fixed Effects**

						95% Confidence Interval	
Parameter	Estimate	SE	*df*	*t*	Sig.	Lower Bound	Upper Bound
Intercept	-0.551	0.193	725.673	-2.859	.004**	0.540	1.297

*Dependent variable: *gm_BYTXSTD*
*$p < .05$, **$p < .01$, ***$p < .001$

Table 3

*Estimates of Covariate Parameters**

					95% Confidence Interval	
Parameter	Estimate	SE	Wald Z	Sig.	Lower Bound	Upper Bound
Residual	70.876	0.940	75.412	.000***	69.058	72.742
Intercept [subject = SCH_ID] Variance	22.763	1.450	15.703	.000***	20.092	25.789

*Dependent variable: *gm_BYTXSTD*
*$p < .05$, **$p < .01$, ***$p < .001$

Next, estimating a level one, individual model will examine the effect of each individual-level independent variable (Heck, Thomas, & Tabata, 2014; Hox, 2002; Raudenbush & Bryk, 2002). Results show that the mean of school test score, after adjusting for student SES, is estimated at 52.457 (or 0.290 above the grand mean of 52.167). In examining the variances

Comment [AJB20]: Nice. Ok. So, you interpreted the change in raw numbers versus the grand mean. That's good. If you left the outcome variable though as it was in the dataset, it'd be fine to have the coefficient come out to 51.576 and you'd interpret it here in a similar way. But, as you're doing kind of both here, it's fine and this is a good way to state it.

Deleted: s

Deleted: vary

Comment [AJB21]: Well stated using the appropriate APA format.

Comment [AJB22]: For your tables you're not using APA format. Instead you're copy and pasting SPSS. It's "ok" for this assignment, at least for this table (we'll see about below), but the problem is that there end up being a bunch of info you don't need.

Check out these two books on the requirements for reporting this type of information, and the specifics on what you need and what you don't need to report. Right now, there's too much in many of these tables. Also, please refer to the examples provided from the past students as well as the articles read for class, as you'll see none of the tables in those examples are direct SPSS output.

Miller, J. E. (2013) The Chicago Guide to Writing about Multivariate Analysis, Second Edition. University Of Chicago Press: Chicago. http://www.amazon.com/Chicago-Writing-Multivariate-Analysis-Publishing/dp/0226527875

Hancock & Mueller (2010) The Reviewer's Guide to Quantitative Methods in the Social Sciences. http://www.amazon.com/Reviewers-Quantitative-Methods-Social-Sciences/dp/041596508X

That said, having the raw SPSS output like these tables in an Appendix for this assignment is a requirement, but in the appendix, where ...

Comment [AJB23]: And here's one of the reasons why, as this table is more about the guts of what's going on in the HLM output. You've already reported this information in the narrative, and don't need this table. Also, you can't have a p-value of 0, which is what you ...

Comment [AJB24]: This is a nice clear structure and a good flow.

Comment [AJB25]: Please don't use passive sentence construction. You can say "I" and should often.

within and between schools, the individual model shows a reduction in variance. In comparing the one-way ANOVA in the null model and the individual model, the results of a reduction in variance estimate indicate that socioeconomic background accounts for approximately 8% of the interschool variability in test scores. Likewise, after socioeconomic status is accounted for in the model, the variance in test scores between schools is 50%, which suggests that half of the variance in mean test scores between schools can be associated with student socioeconomic status. The ICC calculated from Table 5 is 0.148 or 14.8%. Both the ICC and the significant variance in test scores in schools (Wald Z = 73.602, $p < .001$) and between schools (Wald Z = 12.964, $p < .001$) indicate that after controlling for SES, there is significant variability to be explained by other school-level covariates.

Table 4

*Estimates of Fixed Effects**

						95% Confidence Interval	
Parameter	Estimate	SE	df	t	Sig.	Lower Bound	Upper Bound
Intercept	0.290	0.148	671.174	1.964	.050*	7.489E-5	0.580
gm_BYSES2	4.688	0.116	10944.681	40.331	.000***	4.456	4.915

*Dependent variable: gm_BYTXSTD
*$p < .05$, **$p < .01$, ***$p < .001$

Table 5

*Estimates of Covariate Parameters**

					95% Confidence Interval	
Parameter	Estimate	SE	Wald Z	Sig.	Lower Bound	Upper Bound
Residual	65.296	0.887	73.602	.000***	63.580	67.058
Intercept [subject = SCH_ID] Variance	11.357	0.876	12.964	.000***	9.764	12.211

*Dependent variable: gm_BYTXSTD
*$p < .05$, **$p < .01$, ***$p < .001$

Finally, adding the school-level variables can help explain school variation in test scores (Heck, Thomas, & Tabata, 2014; Hox, 2002; Raudenbush & Bryk, 2002). Results in table 6

Comment [AJB26]: Do you mean within school? If so, say it please. This term is confusing. Also, you might have meant intraschool.

Comment [AJB27]: So… your level 1 SES variable explained 8% of the within school level 1 variance in test scores and 50% of the between school variance? The 8% seems really small given the past literature. Hmmm… Your calculations though from the residual tables seem right though.

Comment [AJB28]: Ah, ok. I see what you're doing here, but you've already stated with the null model that the ICC is significant. You don't need to state it again as you add parameters.

Comment [AJB29]: As you build your model forward, please provide a single table with the main models that have predictors so that your reader can examine the coefficents and fit for each one across each model. Also, please present the standardized coefficient, calculated using the equation from Hox that I noted in class and provide that along with the unstandardized coefficient from the "estimate" column.

Please see the example articles for formatting examples.

reveal that school type affects achievement ($\gamma_{01} = 2.970$, $p < .001$), with private/Catholic having higher composite reading and mathematics scores. Also, not being an urban school also affects achievement ($\gamma_{02} = 1.531$, $p < .01$), with suburban and rural schools together having higher composite reading and mathematics scores. In terms of the research question, results in Table 6 indicate that there is no evidence that the presence of computers in the school and school-sponsored teacher training have an effect on student achievement scores in mathematics and reading. These results verify the hypothesis that both variables alone do not have a direct effect on student test scores.

Table 6

*Estimates of Fixed Effects**

						95% Confidence Interval	
Parameter	Estimate	SE	df	t	Sig.	Lower Bound	Upper Bound
Intercept	-3.672	0.977	565.565	-3.756	.000***	-5.593	-1.752
[public=0]	2.970	0.388	604.332	7.660	.000***	2.209	3.732
[public=1]	0	0	-	-	-	-	-
[urban=0]	1.531	0.449	584.829	3.408	.001**	0.649	2.414
[urban=1]	0	0	-	-	-	-	-
[suburban=0]	0.425	0.403	567.849	1.053	.293	-0.367	1.217
[suburban=1]	0	0	-	-	-	-	-
gm_BYSES2	4.542	0.125	10053.855	36.252	.000***	4.297	4.788
BYA43D	0.821	0.501	586.070	1.639	.102	-0.163	1.805
BYA44C	1.441	0.823	576.291	1.751	.081	-0.176	3.059

*Dependent variable: gm_BYTXSTD
**p* < .05, ***p* < .01, ****p* < .001

Table 7

*Estimates of Covariate Parameters**

					95% Confidence Interval	
Parameter	Estimate	SE	Wald Z	Sig.	Lower Bound	Upper Bound
Residual	65.134	0.940	69.292	.000***	63.317	67.002
Intercept [subject = SCH_ID] Variance	9.97	0.848	11.758	.000***	8.443	11.783

*Dependent variable: gm_BYTXSTD
**p* < .05, ***p* < .01, ****p* < .001

Comment [AJB30]: Nice. Carefully stated.

Comment [AJB31]: Please provide a narrative account for the "average" school. For a student at the average in an average school in your model, they have a score that's 3.672 points below the mean, are in a private school, in a rural setting… etc.

Comment [AJB32]: See above on reformatting these tables all the 0's and blanks are confusing.

Please report the standardized coefficients as well. Only for significant parameters though.

Comment [AJB33]: Note that you've loaded these dichotomous variables into the factors section and so SPSS has automatically assumed that 1 is the reference group. I believe you want 0 to be the reference group, so load them in as covariates. That way the equation represents public schools, etc.

Comment [AJB34]: I can't really figure out what the reference group is here, as SPSS is using the 1's as the automatic reference group. That suburban is not significant is a problem, as it should be sig.

Comment [AJB35]: In these tables, don't use the ELS variables, as your reader doesn't remember what they are. Use a brief phrase to tell us what this is, that you setup in the descriptives table.

Limitations

The study has limitations in establishing causality, missing data, and variable selection. Multilevel modeling is not used to establish causality; rather, in order to establish conclusions about school-level variables on student-level outcomes, an experimental design methodology should be used. Furthermore, typically the threshold for missing data is 5% - 10%; however, missing data caused a listwise deletion of approximately 36% of the data, which might have skewed the results of the analysis (Strayhorn, 2009). Listwise deletion of cases was used because it could not be assumed that missing data was random in nature. Further work with data imputation could help alleviate the problems with missing data. Finally, robust variable selection could provide a better picture of technology and its effects on student achievement. Considering other student-level variables, such as if students use computers in class or if students use computers to complete schoolwork, as well as other school-level variables, such as computer and professional development expenditures, could provide a more complete picture of the direct effect in question.

Comment [AJB36]: Good.

Discussion and Implications

The goal of this study was to further explore the assumptions of school-level, technology-related variables on student outcomes. From the study, there is no evidence that the presence of school-sponsored technology training or even having computers in classrooms have a direct effect on student test scores. In further examining the Lesgold (2003) theory-driven causal model, more work should be done in explicating how the implementation of technology professional development could lead to improved test scores. In fact, in the general professional development literature, studies have found that teachers need approximately 49 consistent hours of professional learning in one focus area in order to see a small effect in student outcomes

(Garet, Porter, Desimone, Birman, & Yoon, 2001; Yoon, Duncan, Lee, Scarloss, & Shapley, 2007). In terms of technology training, studies also reveal that singleton, one-time workshops are largely ineffective, yet the majority of technology professional learning experiences are designed in this manner (Guskey, 2001; Kopcha, 2012; Meier, 2005). Consequently, teachers, administrators, and school technology leaders must keep in mind that simply *having and doing* technology-focused professional development in schools is a futile effort; rather, these leaders must innovate solutions toward the quality, structure, and focus of long-term, scaffolded technology professional development.

In addition, the results of this study also reveal questions and inconsistencies on how student achievement and outcomes are assessed, particularly in technology-infused environments. Simply put, there are two paradigms pertaining to technology and testing: 1) Technology as a tool to test; and, 2) Technology as a tool to enhance the content to be tested (Popham, 2001; Wenglinsky, 2005). It has been established that computers do not affect student achievement on standardized tests; therefore, the first paradigm has essentially become antiquated and disproven. Therefore, using technology as a tool to enhance the base level content knowledge should be ideal goal (Dexter, Doering, & Riedel, 2006). Nonetheless, this very study reveals the gaps in national data on how student achievement is measured. If the proper use of technology in the classroom attempts to facilitates a more constructivist approach to teaching and learning (Ertmer, 2005; Fullan, 2013; Larson, Miller, & Ribble, 2010), professional development that is aligned to this goal, as well as additional, more robust measures of success in national data sets are needed in order to holistically assess the presence and use of educational technology and its effect on teaching and learning environments. The conclusions from this study and others suggest that technology integration really has little direct effect on current measures of student-level outcomes. However, if those measures were to change or become more inclusive of different learning experiences and outcomes, assessing the impact of educational technology on student achievement might stand a fighting chance.

Comment [AJB37]: Overall this is a very good start on the Midterm. However, there are multiple issues that I encourage you to address in a revision. First, please see the comments in the methods to list additional information throughout. Second, please see the results section for comments on presenting the information in the appropriate APA format. Also, third, I am concerned about some of the effects reported, but as presented it is somewhat difficult to figure out the extent that the model is correct or not. Please attend to these issues throughout as noted in the comments.

Currently this paper is a B+ (88%), however through a revision in which you substantively address all of the issues in the assignment, I believe that this paper could become a very strong A, if not an A+. Please return a revision anytime by email on or before April 20.

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Appendix A – Raw SPSS Output and Assumption Checks

Descriptives

			Statistic	Std. Error
CASE_ID	Mean		9935.2183	35.67684
	95% Confidence Interval for Mean	Lower Bound	9865.2848	
		Upper Bound	10005.1519	
	5% Trimmed Mean		9928.8854	
	Median		9804.0000	
	Variance		13111491.206	
	Std. Deviation		3620.97932	
	Minimum		3820.00	
	Maximum		16164.00	
	Range		12344.00	
	Interquartile Range		6454.00	
	Skewness		.032	.024
	Kurtosis		-1.242	.048
Student ID	Mean		278806.28	1060.603
	95% Confidence Interval for Mean	Lower Bound	276727.29	
		Upper Bound	280885.27	
	5% Trimmed Mean		278733.18	
	Median		276205.00	
	Variance		11587380809.387	
	Std. Deviation		107644.697	
	Minimum		101101	
	Maximum		461231	
	Range		360130	
	Interquartile Range		196109	
	Skewness		.013	.024
	Kurtosis		-1.281	.048
Link to first follow-up school	Mean		2787.92	10.606
	95% Confidence Interval for Mean	Lower Bound	2767.13	
		Upper Bound	2808.71	
	5% Trimmed Mean		2787.19	
	Median		2762.00	
	Variance		1158742.934	
	Std. Deviation		1076.449	
	Minimum		1011	
	Maximum		4612	
	Range		3601	
	Interquartile Range		1961	
	Skewness		.013	.024
	Kurtosis		-1.281	.048
Standardized test composite score-math/reading	Mean		52.1269	.09537
	95% Confidence Interval for Mean	Lower Bound	51.9399	
		Upper Bound	52.3138	
	5% Trimmed Mean		52.2607	
	Median		52.6600	
	Variance		93.697	
	Std. Deviation		9.67974	
	Minimum		20.91	
	Maximum		81.04	
	Range		60.13	
	Interquartile Range		13.57	

	Skewness		-.212	.024
	Kurtosis		-.296	.048
Socio-economic status composite, v.2	Mean		.1217	.00736
	95% Confidence Interval for Mean	Lower Bound	.1073	
		Upper Bound	.1361	
	5% Trimmed Mean		.1166	
	Median		.0800	
	Variance		.558	
	Std. Deviation		.74694	
	Minimum		-2.11	
	Maximum		1.98	
	Range		4.09	
	Interquartile Range		1.10	
	Skewness		.130	.024
	Kurtosis		-.581	.048
Teacher training on integrating computer into class	Mean		.8809	.00319
	95% Confidence Interval for Mean	Lower Bound	.8746	
		Upper Bound	.8871	
	5% Trimmed Mean		.9232	
	Median		1.0000	
	Variance		.105	
	Std. Deviation		.32394	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		.00	
	Skewness		-2.352	.024
	Kurtosis		3.533	.048
Computers in classrooms	Mean		.9581	.00198
	95% Confidence Interval for Mean	Lower Bound	.9542	
		Upper Bound	.9619	
	5% Trimmed Mean		1.0000	
	Median		1.0000	
	Variance		.040	
	Std. Deviation		.20046	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		.00	
	Skewness		-4.571	.024
	Kurtosis		18.898	.048
Public	Mean		.7596	.00421
	95% Confidence Interval for Mean	Lower Bound	.7514	
		Upper Bound	.7679	
	5% Trimmed Mean		.7885	
	Median		1.0000	
	Variance		.183	
	Std. Deviation		.42733	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		.00	
	Skewness		-1.215	.024
	Kurtosis		-.523	.048
Urban	Mean		.3051	.00454
	95% Confidence Interval for Mean	Lower Bound	.2962	
		Upper Bound	.3140	

	5% Trimmed Mean		.2835	
	Median		.0000	
	Variance		.212	
	Std. Deviation		.46048	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		1.00	
	Skewness		.847	.024
	Kurtosis		-1.284	.048
Suburban	Mean		.4971	.00493
	95% Confidence Interval for Mean	Lower Bound	.4875	
		Upper Bound	.5068	
	5% Trimmed Mean		.4968	
	Median		.0000	
	Variance		.250	
	Std. Deviation		.50002	
	Minimum		.00	
	Maximum		1.00	
	Range		1.00	
	Interquartile Range		1.00	
	Skewness		.011	.024
	Kurtosis		-2.000	.048

```
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Correlations[c]

		Standardized test composite score-math/reading	Socio-economic status composite, v.2	Teacher training on integrating computer into class	Computers in classrooms	School control	School urbanicity
Standardized test composite score-math/reading	Pearson Correlation	1	.444**	.001	.001	.207**	-.026**
	Sig. (2-tailed)		.000	.896	.917	.000	.007
Socio-economic status composite, v.2	Pearson Correlation	.444**	1	-.017	-.037**	.307**	-.096**
	Sig. (2-tailed)	.000		.077	.000	.000	.000
Teacher training on integrating computer into class	Pearson Correlation	.001	-.017	1	.364**	-.253**	.025*
	Sig. (2-tailed)	.896	.077		.000	.000	.010
Computers in classrooms	Pearson Correlation	.001	-.037**	.364**	1	-.154**	-.027**
	Sig. (2-tailed)	.917	.000	.000		.000	.007
School control	Pearson Correlation	.207**	.307**	-.253**	-.154**	1	-.266**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
School urbanicity	Pearson Correlation	-.026**	-.096**	.025*	-.027**	-.266**	1

Sig. (2-tailed)	.007	.000	.010	.007	.000	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
c. Listwise N=10301

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  /NOTOTAL.
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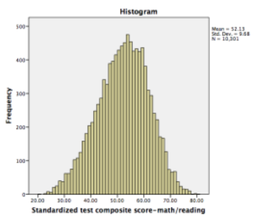
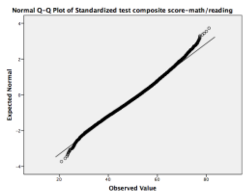
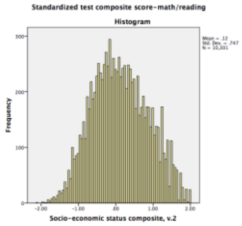
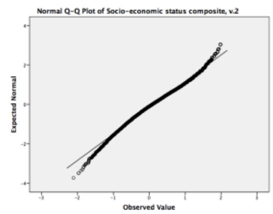
Case Processing Summary

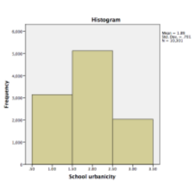
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Standardized test composite score-math/reading	10301	63.6%	5896	36.4%	16197	100.0%
Socio-economic status composite, v.2	10301	63.6%	5896	36.4%	16197	100.0%
Teacher training on integrating computer into class	10301	63.6%	5896	36.4%	16197	100.0%
Computers in classrooms	10301	63.6%	5896	36.4%	16197	100.0%
School control	10301	63.6%	5896	36.4%	16197	100.0%
School urbanicity	10301	63.6%	5896	36.4%	16197	100.0%

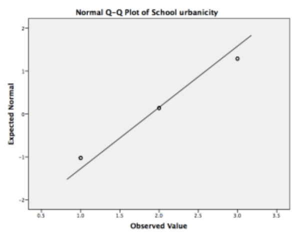












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  DATA: BYSES2=col(source(s), name("BYSES2"))
  DATA: BYA43D=col(source(s), name("BYA43D"))
  DATA: BYA44C=col(source(s), name("BYA44C"))
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  GUIDE: axis(dim(2.1), ticks(null()))
  GUIDE: axis(dim(1), gap(0px))
  GUIDE: axis(dim(2), gap(0px))
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  TRANS: BYSES2_label = eval("Socio-economic status composite, v.2")
  TRANS: BYA43D_label = eval("Teacher training on integrating computer into class")
  TRANS: BYA44C_label = eval("Computers in classrooms")
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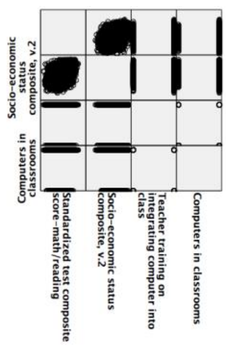


```
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  /NOORIGIN
  /DEPENDENT BYTXCSTD
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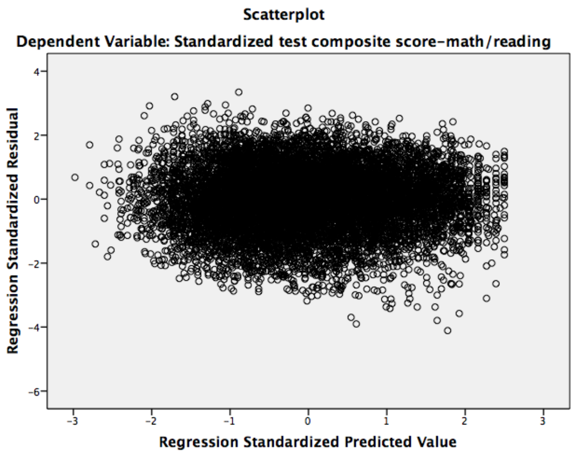
Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	50.591	.428		118.245	.000		
	Socio-economic status composite, v.2	5.762	.114	.445	50.330	.000	.999	1.001
	Teacher training on integrating computer into class	.093	.283	.003	.327	.744	.867	1.153
	Computers in classrooms	.787	.458	.016	1.717	.086	.866	1.154

a. Dependent Variable: Standardized test composite score-math/reading

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MIXED gm_BYTXCSTD
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ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
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Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	725.673	8.175	.004

a. Dependent Variable: gm_BYTXCSTD.

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.550587	.192562	725.673	-2.859	.004	-.928632	-.172543

a. Dependent Variable: gm_BYTXCSTD.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		70.876486	.939862	75.412	.000	69.058123	72.742729
Intercept [subject = SCH_ID]	Variance	22.763082	1.449576	15.703	.000	20.092116	25.789115

a. Dependent Variable: gm_BYTXCSTD.

```
MIXED gm_BYTXCSTD WITH gm_BYSES2
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ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
  /FIXED=gm_BYSES2 | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(SCH_ID) COVTYPE(VC).
```

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.289903	.147608	671.174	1.964	.050	7.489104E-5	.579731
gm_BYSES2	4.687548	.116228	10944.681	40.331	.000	4.459719	4.915376

a. Dependent Variable: gm_BYTXCSTD.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		65.296269	.887150	73.602	.000	63.580435	67.058408
Intercept [subject = SCH_ID]	Variance	11.357161	.876038	12.964	.000	9.763648	13.210749

a. Dependent Variable: gm_BYTXCSTD.

```
MIXED gm_BYTXCSTD BY Public Urban Suburban WITH gm_BYSES2 BYA43D BYA44C
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1) SINGULAR(0.000000000001) HCONVERGE(0,
ABSOLUTE) LCONVERGE(0, ABSOLUTE) PCONVERGE(0.000001, ABSOLUTE)
  /FIXED=Public Urban Suburban gm_BYSES2 BYA43D BYA44C | SSTYPE(3)
  /METHOD=REML
  /PRINT=G  SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(SCH_ID) COVTYPE(VC).
```

Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-3.672594	.977752	566.565	-3.756	.000	-5.593056	-1.752133
[Public=.00]	2.970387	.387781	604.332	7.660	.000	2.208826	3.731948
[Public=1.00]	0[b]	0	.	.	.	.	.
[Urban=.00]	1.531444	.449433	584.829	3.408	.001	.648744	2.414144
[Urban=1.00]	0[b]	0	.	.	.	.	.
[Suburban=.00]	.424743	.403223	567.849	1.053	.293	-.367248	1.216734
[Suburban=1.00]	0[b]	0	.	.	.	.	.
gm_BYSES2	4.542350	.125299	10053.855	36.252	.000	4.296739	4.787961
BYA43D	.821134	.501141	586.070	1.639	.102	-.163117	1.805386
BYA44C	1.441487	.823304	576.291	1.751	.081	-.175556	3.058529

a. Dependent Variable: gm_BYTXCSTD.
b. This parameter is set to zero because it is redundant.

Estimates of Covariance Parameters[a]

Parameter		Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Residual		65.133566	.939981	69.292	.000	63.317048	67.002198
Intercept [subject = SCH_ID]	Variance	9.974035	.848252	11.758	.000	8.442665	11.783171

a. Dependent Variable: gm_BYTXCSTD.