The Effects of Technology on Reading Performance in the Middle-School Grades: A Meta-Analysis With Recommendations for Policy

November 2005

P. David Pearson
University of California Berkeley

Richard E. Ferdig
University of Florida

Robert L. Blomeyer, Jr.
North Central Regional Educational Laboratory

Juan Moran
University of Illinois

1120 East Diehl Road, Suite 200
Naperville, IL 60563-1486
800-356-2735 • 630-649-6500
www.learningpt.org

Copyright © 2005 Learning Point Associates, sponsored under government contract number ED-01-CO-0011. All rights reserved.

This work was originally produced in whole or in part by the North Central Regional Educational Laboratory® (NCREL®) with funds from the Institute of Education Sciences (IES), U.S. Department of Education, under contract number ED-01-CO-0011. The content does not necessarily reflect the position or policy of IES or the Department of Education, nor does mention or visual representation of trade names, commercial products, or organizations imply endorsement by the federal government.

NCREL remains one of the 10 regional educational laboratories funded by the U.S. Department of Education and its work is conducted by Learning Point Associates.

Learning Point Associates, North Central Regional Educational Laboratory, and NCREL are trademarks or registered trademarks of Learning Point Associates.
# Contents

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
</tr>
<tr>
<td>Background for the Meta-Analysis</td>
</tr>
<tr>
<td>The Evolving Relationship Between Literacy and Technology</td>
</tr>
<tr>
<td>Concerns About Literacy, Technology, and Adolescents</td>
</tr>
<tr>
<td>The Context for the Synthesis</td>
</tr>
<tr>
<td>Method</td>
</tr>
<tr>
<td>Inclusion Criteria</td>
</tr>
<tr>
<td>Location and Selection of Publications</td>
</tr>
<tr>
<td>The Filtering Process for the Selection of the Target Articles</td>
</tr>
<tr>
<td>Statistical Treatment</td>
</tr>
<tr>
<td>Results and Discussion</td>
</tr>
<tr>
<td>Descriptive Results</td>
</tr>
<tr>
<td>Analysis of Effect Sizes</td>
</tr>
<tr>
<td>Examining Simple Effects Within Categories</td>
</tr>
<tr>
<td>Summary of Results</td>
</tr>
<tr>
<td>Suggestions for Policy and Practice</td>
</tr>
<tr>
<td>Recommendations for Practice</td>
</tr>
<tr>
<td>Recommendations for Future Research</td>
</tr>
<tr>
<td>References</td>
</tr>
</tbody>
</table>

## Appendixes

<table>
<thead>
<tr>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Appendix A. Keywords Used for Web Searches</td>
</tr>
<tr>
<td>Appendix B. Academic and Educational Databases</td>
</tr>
<tr>
<td>Appendix C. Educational Technology and Reading Journals</td>
</tr>
<tr>
<td>Appendix D. International Journals</td>
</tr>
<tr>
<td>Appendix E. Meta-Analysis Coding for Reading and Technology Studies</td>
</tr>
<tr>
<td>Appendix F. Statistics for the 89 Effect Sizes in the Analysis</td>
</tr>
<tr>
<td>Appendix G. Bibliographies</td>
</tr>
</tbody>
</table>
Abstract

This article reports the results of a meta-analysis of 20 research articles containing 89 effect sizes related to the use of digital tools and learning environments to enhance literacy acquisition. Results (weighted effect size of 0.489) demonstrate that technology can have a positive effect on reading comprehension, but little research has focused on the effect of technology on metacognitive, affective, and dispositional outcomes. We conclude that although there is reason to be optimistic about using technology in middle-school literacy programs, there is also reason to encourage the research community to redouble its emphasis on digital learning environments for students in this age range and to broaden the scope of the interventions and outcomes they study.
Background for the Meta-Analysis

Literacy, and reading in particular, is just one of the many areas in which research has provided evidence of the potential impact of new technologies such as multimedia and hypermedia. Unfortunately, most of the studies in this research corpus have addressed literacy or reading acquisition in the early years of schooling. These technologies may be equally as important for older readers, particularly those who have not experienced great success in their school careers. To assess our collective and cumulative knowledge about the impact of digital tools on the reading performance of middle-school students, we conducted a meta-analysis.

The primary purpose of this work was to determine whether digital technologies can affect the acquisition of advanced reading skills, such as comprehension, metacognition, strategy use, and motivation and engagement. Another purpose was to identify, or at least to point in the direction of, substantive (i.e., topics or skills are being taught), technical, and contextual factors associated with effective interventions. The ultimate outcomes of this second purpose, we hoped, would be a set of implications to guide policy makers in their quest to improve reading acquisition in these vexing middle-school years and a menu of promising pathways to guide future research.

The Evolving Relationship Between Literacy and Technology

Literacy and technology are two words that seem to be increasingly paired in today’s worlds of research, practice, and policy. People often describe the need to become computer literate; authors write about digital literacy (and related terms such as visual literacy and media literacy) as one of the important new discourses in our schools; and research has investigated the role of technology in improving literacy acquisition and instruction.

The first of these issues, the need to become computer literate, is very real in the policy and practice of today’s schools. The National Educational Technology Standards (NETS), for instance, have been developed to ensure that children are learning with technology and using digital tools to acquire knowledge in content areas (ISTE, 2005). The International Reading Association suggested the following rights in a 2001 position statement on literacy and technology:

- Teachers who are skilled in the effective use of Information Communications Technology (ICT) for teaching and learning
- A literacy curriculum that integrates the new literacies of ICT into instructional programs
- Instruction that develops the critical literacies essential to effective information use
- Assessment practices in literacy that include reading on the Internet and writing using word-processing software
- Opportunities to learn safe and responsible use of information and communication technologies
- Equal access to ICT
Such goals and standards include not just attaining comfort with and knowledge of the machine, but also related literacies including information literacy, visual literacy, digital literacy, new literacy, critical literacy and media literacy (Holum & Gahala, 2001).

As one looks broadly at the interface of technology and literacy, perhaps most potentially rewarding for literacy educators is the role of technology in literacy acquisition and instruction, especially for primary grade populations. We know, for example, that electronic storybooks help improve student comprehension and motivation (Matthew, 1997; Doty, Popplewell, & Byers, 2001) and that they also provide immediate decoding feedback to students (Labbo & Kuhn, 1998; deJong & Bus, 2002; Cazet, 1998; Doty, Popplewell, & Byers, 2001).

In addition to electronic storybooks, teachers use software such as KidPix (Labbo, Eakle, & Montero, 2002), Hyperstudio, and Microsoft PowerPoint to help students learn to decode. Websites such as Hot Potatoes (http://web.uvic.ca/hrd/halfbaked/) and Enchanted Learning (http://www.enchantedlearning.com/Home.html) provide cloze exercises and paragraph, sentence, and letter scramblers. PBS Kids & Sesame Street’s Letter of the Day (http://pbskids.org/sesame/letter/), Scholastic’s Letter Match (http://teacher.scholastic.com/clifford1/flash/confusables/). Even Merriam-Webster’s allegedly lexicographically oriented website (http://www.m-w.com/) provides support for phonemic awareness and instruction. Finally, Leu & Kinzer (1999) have argued that (1) Internet activities, (2) Internet projects, (3) Internet inquiries, and (4) Internet workshops can lead to effective literacy instruction and reading comprehension.

Technology is also used for writing instruction; indeed, the interface of technology and writing is sufficiently sophisticated to have attracted both “best practice” syntheses as well as meta-analysis (Goldberg, Russell & Cook, 2003). The Venn Diagram website (http://www.venndiagram.com/), software tools such as Inspiration and Microsoft PowerPoint, and hardware like Smartboards & Interactive Whiteboards provide students with opportunities to create concept maps and Venn diagrams to organize their writing. E-zines, or electronic magazines, not only provide current and authentic reading material for students, they also publish student work and thus act as an authentic audience for student writing. Electronic portfolios are providing ways for students to showcase their writing to teachers, other students, and parents.

Even simple word processors have ‘tracking changes’ features where students can collaborate in their writing and thus receive scaffolding in their development. Blogs can provide online journaling space for students to write about their growing expertise or their daily observations (Ferdig & Trammell, 2004) and word searches, word games, and online dictionaries and thesauruses build students vocabulary and confidence in language use. Students and teachers also find great writing practice using webquests and inquiry pages. Finally, students get writing practice through authentic projects such as Keypals, where they write with classrooms in different states or countries, and the Internet Project Registry, where classes can register their projects and collaborate with students from around the world.

Beyond reading and writing, technology has been used to increase access to images of and information about diversity in classrooms, both at the student level with projects like I Love
Languages (http://www.iolovelanguages.com/) and Say Hello to the World (http://www.ipl.org/div/kidspace/hello/) and also at the instructor and preservice level with projects like CTELL (Teale, Leu, Labbo, & Kinzer, 2002) and The Reading Classroom Explorer (Ferdig, Roehler, & Pearson, in press). Technology has been used to give struggling readers access to scaffolding and individualized instruction through projects like Technology-Enhanced Literacy Environment-Web (TELE-Web; Zhao, Englert, Jones, Chen, & Ferdig, 2000). Computers and even older media such as audio and video recorders give students practice with spoken language. Free online archives provide reading material for both storytelling and literature classes. Finally, online journals, listservs, discussion forums, and associations provide continued professional development for the literacy instructor.

In short, we have witnessed a proliferation of applications of various sorts of technology for various populations of users from preschoolers to teachers. But have we conducted enough careful research in technology education field to have reached a point of maturity sufficient to merit extensive reviews, such as best-evidence syntheses and meta-analyses of various aspects of technology tools?

We have certainly made those attempts in recent years, but with varying degrees of success. In recent years, Cavanaugh et al. (2004) provided evidence in their meta-analysis that distance education is as effective as face-to-face classroom instruction. Shachar & Neumann (2003) analyzed studies on distance learning and found that distance learners outperformed counterpart students in face-to-face classrooms in two thirds of the studies. Waxman et al. (2003) synthesized the literature on teaching and learning with technology and found it had a positive significant effect on student outcomes when compared to instruction without technology, a finding supported by others in this field (Kulik & Kulik, 1991; Kulik & Kulik, 1986).

Turning to the purview of the present study, there have been a few recent meta-analyses related to literacy and technology. Goldberg, Russell, & Cook (2003) synthesized 26 studies from 1992–2002 and found that computers improved the quality and quantity of writing compared to classrooms without technology. They did find mixed results, however, for revision behaviors. Torgerson, Porthouse, & Brooks (2003) found a modest benefit for computer-assisted instruction for literacy acquisition of imprisoned adults, but it was not statistically significant. Finally, Torgerson & Elbourne (2002) completed a meta-analysis on the effects of Information Communications Technology on spelling, finding what they characterize as a modest but not statistically significant effect favoring technology in the teaching of spelling.

On the specific question of the empirically established relationships between literacy and technology, Leu (in press) has suggested that our scholarship to date warrants at least three distinct conclusions: (a) Technology is transformative, changing the nature of literacy (see also Reinking, 1998); (b) the relation between literacy and technology is transactional (see Bruce, 1997); and (c) technology is deictic, which means that it will change rapidly in response to environmental forces.

Unfortunately, what is less clear is what the research can definitively suggest about the relation between technology and literacy. One problem is the alarmingly low number of published research studies investigating technology and literacy (Leu, in press; Kamil & Lane, 1998). Clearly either more research has to be done or we need a better approach to identifying and...
analyzing relevant existing research. The current endeavor is predicated on the assumption that although we may well need more and better research, it is time to take stock of what we do know, if for no other reason than to highlight gaps to guide the field in future scholarly efforts. And, if the effects we do find are truly powerful, even though limited in scope, we should publicly acknowledge and use what we do know and can recommend to policymakers with confidence.

Concerns About Literacy, Technology, and Adolescents

No Child Left Behind (NCLB) funds reading programs (Reading First) that focus primarily on Prekindergarten through Grade 3; however, the NCLB Act (2002) also requires that students in Grades 4 through 12 make adequate yearly progress toward meeting state reading standards. Additionally, the Reading First provision of NCLB dictates that students who are not making adequate progress in the middle-school years be offered research-based interventions to accelerate their learning. Finally, even though the lion’s share of the resources for improving reading in the context of current policy go to the primary grades, the rhetoric about the need for focusing greater attention and resources on adolescent literacy has been steadily mounting for the past few years.

Several professional organizations, in fact, have championed this shift in attention. For example, the National Reading Conference (NRC) commissioned a white paper on Effective Literacy Instruction for Adolescents (Alvermann, 2001) that explicitly acknowledges the complexities of reading in relation to writing and oral language in an array of 21st-century media environments, including, of course, print. The International Reading Association, in its Position Statement on Adolescent Literacy (2002), echoed this perspective by emphasizing the importance of (a) access to a wide variety of reading materials, (b) building skills and desire to read complex materials, (c) modeling and giving explicit instruction, and (d) developing an understanding of the complexities of individual adolescent readers.

While our empirical knowledge may be weak, individuals have used theoretically based arguments, grounded in best practice and compelling cases, to draw conclusions about the degree to which technology tools can and do support literacy teaching and learning for adolescents. Although Alvermann (2001) cites little empirical research on the topic generally, and even less that applies specifically to instruction at the middle and high school levels, she, along with others, provides relevant examples to illustrate how adolescents are making valuable reading-writing connections in their bid to communicate in a computer-mediated world (e.g., Beach & Bruce, 2002; Beach & Lundell, 1998; Horney & Anderson-Inman, 1994).

Other work suggests that American youth are turning more and more toward the Internet as their primary textbook and spend more time with media than any other single activity (Gee, 2002; Lenhart, Simon, & Graziano, 2001; Levin & Arafeh, 2002). Levin and Arafeh (2002) found, for example, that 71 percent of students pointed to the Internet as their primary resource for completing homework assignments. These same students actually regarded the Internet as more relevant to their daily lives than other forms of information, a finding suggesting that schools are woefully slow on the Internet uptake. We agree with O’Brien (in press) that the widespread use of the Internet and other digital tools among youth requires educators to facilitate students’
experiences with digital literacy tools in school. What we are less certain about, and certainly less knowledgeable about, is the particular focus that facilitative support should take. Indeed, the fact that so many scholars of adolescent literacy resort to compelling cases to support their policy and practice recommendations about literacy underscores the need for precisely the sort of synthesis we have undertaken.

The Context for the Synthesis

Commissioned by the North Central Regional Educational Laboratory (NCREL) Center for Technology, in collaboration with the NCREL Center for Literacy, we conducted a research synthesis of experimental and quasi-experimental studies, conducted within the last decade and a half of the start of the project (1988 was set as the cut off), that focus on interventions using digital literacy tools to improve the reading performance of middle school students. To narrow the research synthesis topic from the original and broad topic of “the effectiveness of technology on student achievement in literacy” found in NCREL’s 2004 Updated Annual Plan, we looked at the What Works Clearinghouse (WWC) topic areas to ensure that we were not duplicating efforts in place by WWC developers. We considered topics that could contribute to the WWC as well as continue to inform the work of NCREL’s Center for Technology and Center for Literacy for the foreseeable future; hence the current emphasis on the impact of digital tools on adolescent reading.

Specifically, our research synthesis set out to use the tools of meta-analysis to answer questions about five areas designated in the request for proposals from the funding agency on the grounds that their answers would provide information essential to improved reading performance for adolescents: the impact of digital literacy tools on middle-school students in the following areas:

- Strategy use
- Metacognition
- Reading motivation
- Reading engagement
- Reading comprehension

We sought studies that attempted to both improve and measure progress in one or more of these areas. We defined digital literacy tools broadly to include a wide range of the use of media forms—images, video and audio clips, hypertext, hypermedia, Web pages, learning environments, and particular formats of presenting information for student learning. Of particular interest were the media forms of hypertext, hypermedia, and Web pages; we hoped that we would find a substantial body of experimental and quasi-experimental work examining these particular forms. This focus was strategic and intentional. We knew that the concepts of hypertext and hypermedia are considered crucial to understanding the interactions between reader and text in a multimedia environment. Additionally, the conventional wisdom about the effect of hypertext and other media on reading performance, especially in content area reading, is optimistic and enthusiastic (Vacca & Vacca, in press). We wanted to know whether such a high level of enthusiasm is supported by the available evidence.
Method

Inclusion Criteria

A study was included in this meta-analysis if it met the following criteria:

- Was subjected to a peer review process. This excluded studies such as doctoral dissertations, conference presentations, and unpublished reports, but it did include prepublication project reports that were peer-reviewed.
- Included students in the middle grade school levels (6th, 7th, and 8th grade). Those studies that only reported results on these levels were labeled “right on target.” There were studies that included earlier or later grades along with the middle level grades. Where possible we only used the effect size data from the target grade levels. Occasionally when data could not be disaggregated (e.g., Grades 5–7 were lumped together), we spilled over into adjacent grade levels.
- Used technology as the independent or moderating variable in the examination of reading skills.
- Reported outcomes assessing the impact of a treatment on reading comprehension, metacognition, strategy use, and/or motivation.
- Used an experimental or quasi-experimental design, including pretest-posttest designs.
- Reported sufficient statistics to permit the calculation of an effect size.
- Was published between 1988–2005. The time period was decided upon to address articles that had not been reviewed in previous and broader meta-analyses on the relationship between technology and reading processes.

Location and Selection of Publications

In an effort to be inclusive (and to take advantage of work conducted around the world) the search process was purposefully broadened to include studies from as many countries, languages, and cultural ranges as possible. We searched and included studies from many geographical areas as well as studies written in Spanish (one of the authors is a native Spanish speaker). It should be noted that most of the international journals consulted publish in English. We found a few candidate studies in Spanish, one of which survived into the final pool; many candidates and several finalists came from research conducted outside North America.

An exhaustive search of databases, journals, websites, and bibliographic resources was carried out for studies that could even plausibly meet the established inclusion criteria. Five main searches were completed. First, drawing on various combinations of keywords (Appendix A), web searches were performed using such search engines as Google, Google Scholar, Yahoo, Metacrawler, Search.com, AskJeeves, AltaVista and Lycos. Second, similar keywords were used to systematically search academic and educational databases (Appendix B). The third search method was to examine abstracts in 79 educational technology, special education, psychology, literacy, and reading journals both in print and electronic modes, as not all journals or issues are available electronically (Appendix C). Fourth, in an effort to cover other cultural and linguistic
ranges, abstracts in 34 relevant international journals were searched (Appendix D). Finally, Web sites of several reading and education professional organizations and research institutes were browsed for studies. Examples of such sites are the various regional educational laboratories, the Center for Research on Evaluation, Standards, and Student Testing, the research centers for various states departments of education, the Rand Corporation, and federal institutes such as the National Institute of Child Health and Human Development.

The Filtering Process for the Selection of the Target Articles

The initial strategy for this search process was extensive rather than intensive. The goal was to identify the maximum number of studies and articles that met or even came close to meeting the inclusion criteria. “Backward mapping” was also used; we consulted the references at the end of target articles for potential other studies. Finally, literacy and technology experts (operationally defined as individuals whose works we encountered searching the literature, both in the U.S. and abroad, were contacted to solicit advice and information on studies not found in the searches or in the journals examined.1

From this initial filtering stage, 204 full-text candidate articles or reports were obtained and evaluated for inclusion in the analysis. These 204 articles were subjected to a second screening that included four key criteria. First, the type of study was examined to determine if the study was experimental, quasi-experimental, a natural experiment, a literature review, a correlation study, or a qualitative study. We were interested only in experimental or quasi-experimental studies as is appropriate and necessary for conducting a meta-analysis. Second, the grade level of the subjects were coded; only articles that had at least some subjects in Grades 6–8 were included. Next, articles were included if the content of the study was at least partially related to reading (rather than writing, language arts, or some other content interest), in terms of the intervention and the outcome. Finally, articles were coded for the use of the technology in the study. Articles were not included in the meta-analysis if technology was not used or if the use of technology was incidental. Each article was read by at least two of the four authors of the report. When we applied these four criteria, our sample was reduced from 204 to 38.

The third filtering stage occurred when we used the criteria from the coding manual developed by Waxman and his colleagues (2003) for NCREL. In the process of applying these criteria, which included the computation of effect sizes for each dependent measure, the set of articles was trimmed to the 20 that eventually were used in the meta-analysis. Several studies did not have sufficient data to compute the effect size or had reported results without control or treatment statistics. The complete Waxman-derived codebook is located in Appendix E. For both the second and third filters, we consulted the criteria included in the “Study Review Standards” from the What Works Clearinghouse (What Works Clearinghouse, n.d.); in fact, many of the standards in the third (i.e., Waxman, 2003) filter are identical to those proposed by

1 See Appendix G for a full bibliography of studies reviewed.
Table 1 provides a summary of the major categories and the variables that were examined in depth in this meta-analysis.

<table>
<thead>
<tr>
<th>Major Category</th>
<th>Brief Description of the Major Category</th>
<th>No. of Variables</th>
<th>Variables Examined In-depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study Characteristics</td>
<td>This category contained descriptive information about the study. It included the name, year, and author(s) of the article. It also included variables like gender, country, region, ethnicity, and target audience.</td>
<td>17</td>
<td>Author&lt;br&gt;Year&lt;br&gt;# of comparisons&lt;br&gt;Student sample size&lt;br&gt;Journal of Publication&lt;br&gt;Target Population</td>
</tr>
<tr>
<td>Study of Quality Indicators</td>
<td>Variables within this category related to the factors helping determine the quality of the study. These variables included the name of the measure and its reliability, the pretest equivalency, and various outcomes.</td>
<td>12</td>
<td>Duration of study&lt;br&gt;Cognitive outcomes&lt;br&gt;Affective outcomes&lt;br&gt;Behavioral outcomes&lt;br&gt;Effect size coefficient&lt;br&gt;Weight</td>
</tr>
<tr>
<td>Sources of Invalidity</td>
<td>History, maturation, selection bias, type of design, and selection-maturation interaction are all examples of sources of invalidity that were coded in this category.</td>
<td>14</td>
<td>The sources of invalidity in the codebook provided a way to examine whether the methodologies provided in the studies were rigorous enough to include the results in the meta-analysis. As such, all 14 variables were examined to help filter the selected corpus of articles.</td>
</tr>
<tr>
<td>Reading Characteristics</td>
<td>The reading characteristics category included variables to describe both the focus of the intervention (what they did) and the outcome of the intervention (what they observed).</td>
<td>2</td>
<td>Examples of potential codes for the two variables included:&lt;br&gt;Phonics&lt;br&gt;Phonemic awareness&lt;br&gt;Vocabulary&lt;br&gt;Reading comprehension&lt;br&gt;Reading Volume&lt;br&gt;Reader response&lt;br&gt;Fluency&lt;br&gt;Independent reading&lt;br&gt;Meta-cognition&lt;br&gt;Content Learning&lt;br&gt;Spelling&lt;br&gt;Word Recognition</td>
</tr>
</tbody>
</table>

The Effects of Technology on Reading Performance in the Middle-School Grades: A Meta-Analysis With Recommendations for Policy—9
<table>
<thead>
<tr>
<th>Major Category</th>
<th>Brief Description of the Major Category</th>
<th>No. of Variables</th>
<th>Variables Examined In-depth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology Characteristics</td>
<td>The technology characteristics category examined the technology features of the study. Variables included the type of technology used, the role or focus of the technology, and the teacher and students’ prior experience with technology.</td>
<td>19</td>
<td>Aegis of technology</td>
</tr>
<tr>
<td>Instructional / Teaching Characteristics</td>
<td>Instructional and teaching characteristics were examined in this category. Examples include the setting and mode of instruction, collaboration, and what types of conversations where encouraged in the pedagogy.</td>
<td>7</td>
<td>Unfortunately, in many cases, this information was not clearly delineated in the research article. Therefore, no information was gathered from the 20 articles to run meaningful analyses for this category.</td>
</tr>
<tr>
<td>Policy</td>
<td>The final category related to the policy focus of the study. This category contained two variables: the level of policy (i.e. state or national) and the policy focus.</td>
<td>2</td>
<td>Not enough information was included in most articles to analyze the level of policy. The policy focus was examined and included the following possibilities: Unspecified Reducing achievement gaps Increased use of technology Increased specific type of use Improve Specific Educational Outcomes</td>
</tr>
</tbody>
</table>

### Statistical Treatment

To obtain effect sizes, the quantitative results from individual studies were transformed into a standardized difference between the treatment and the control group on a given measure. We calculated the effect sizes by taking the mean performance difference between the group that received technology experimental treatment and the control group and dividing it by a pooled standard deviation. Because it has been documented that this effect-size index tends to be upwardly biased when based on small sample sizes, Hedges’ (1981) correction was applied.

The Hedges correction uses the inverse variance weight to give more weight to studies with larger sample sizes. The Hedges “g” statistic, a weighted effect-size estimate, was used in all subsequent analyses. Two different effect-size calculation methods were utilized depending on the summary statistics reported within the individual research studies: posttest means and standard deviations \((n=16)\) and between-groups independent \(t\) test \((n=4)\). Effect sizes were computed using formulas provided by Lipsey & Wilson (2001); in a few instances, we used \(t\) or \(F\) test statistics to infer appropriate values.
Selecting a Model

The statistical models for meta-analysis are broadly classified into two types: fixed effects and random effects. Fixed-effects models generalize to a hypothetical population of studies, from which one assumes to have drawn a random sample. Random-effects models generalize to a population of subjects. The models differ in the way they treat the variability of the results between the studies.

The fixed-effects model treats variability as exclusively due to random variation; thus if all the studies were infinitely large they would give identical results. The random effects model assumes a different underlying effect for each study and takes this into consideration as an additional source of variation. In general, random effects models are more conservative because they result in wider confidence intervals than the fixed-effects model. In all of our analyses we used the random-effects model particularly due to the small number of studies and the related issues of homogeneity.

Three types of data analyses were performed:

1. For each study, an independent set of effect sizes were extracted, weighted, and then aggregated. Using the combined effect size extracted from each study, an overall effect size across studies was calculated and tested for statistical significance.
2. Analyses were performed to investigate heterogeneity and publication bias of the effect sizes. We utilized homogeneity testing and forest plot depiction.
3. Based on our substantive interests in this area of research, we conducted several comparisons of the extent to which study features (e.g., population served or instructional focus) moderated the effect on outcome measures. For these comparisons we used the total of 89 effect sizes. In doing each of these specific comparisons, we computed a Q statistic to test the difference between effect sizes aggregated for the levels of a given variable (after Lipsey & Wilson, 2001).

We used the weighted average, as recommended in the statistical literature to give more weight to larger studies with less random variation than to smaller studies. The method we used was the inverse variance method where the weights are equal to the inverse of each study’s estimated effect size.

Computing Effect Sizes from Correlated Designs

A consistently vexing question for those who undertake meta-analyses is how to compute effect sizes when there are correlated designs such as matched groups, repeated measures, within-subjects factorial design, and single subject among others. In these designs there are two possibilities to compute the effect size (ES) for a study. One possibility is to use the original standard deviations for the means of two groups (treatment and control). Another possibility is to take into account the correlation between two scores. If we follow the second possibility the calculated effect will be larger than the first possibility (at least when the correlation exceeds 0.5). In our meta-analysis we did explore the calculations for both possibilities. However, the work done by Dunlop, Cortina, Vaslow, and Burke (1996) and Morris and DeShon (2002)
convincingly argues that original standard deviations should be used to compute ES for correlated designs. These authors argued and showed that if the pooled standard deviation is corrected for the amount of correlation between the measures, then the ES estimate will be an overestimate of the actual ES. (For those who are skeptical about this approach, it will be useful to note that we did actually use both approaches and found that when the effect sizes are calculated by taking the correlations into account, none of the major findings and conclusions are altered.)
Results and Discussion

Descriptive Results

The most striking result of the analysis is that we were able to locate data allowing us to address adequately only one of the five areas of reading about which we sought empirical evidence: comprehension. We found only two studies that provided outcome measures for strategy use (Solomon et al., 1999; Reinking, 1988). Interestingly in the Solomon study, the effect sizes were “off the charts” in favor of the technological training over the control group (which received no metacognitive emphasis); by contrast, the effect sizes in the Reinking study were inconsequentially in favor of the control group on strategy use (in the -0.05 to -0.10 range). We could not disentangle strategy use from metacognition (since strategy use is inherently metacognitive) either as an outcome or as an intervention focus, so in the final analysis we grouped them together. Four studies “mentioned” motivation but only two (Kramarski, 2000; Reinking, 1988) included measures of it, and engagement was only reported as a qualitative outcome by a few authors, most often to describe the delight teachers or students took in using the technology.

The overwhelming emphasis was on reading outcomes, with comprehension as the most common of all outcome measures (65 percent); vocabulary, which we viewed as a member of the comprehension family, was a distant second, accounting for 10 percent of the outcomes. In terms of the emphasis of the interventions, the distribution was much more even than for outcomes. Most interventions attended to more than one aspect of reading; hence the highest incidence was for “mixed” emphases at 30 percent of the cases; for example, an environment would offer a hypertext learning environment with access to word pronunciation, word meaning, contextual information, and comprehension scaffolds to guide an individual’s reading.

One might speculate that those who work in this medium are attempting to take full advantage of its capabilities. Among the single emphasis programs, the focus was fairly evenly distributed among vocabulary (17 percent), word recognition (15 percent), independent reading (12 percent), and comprehension instruction (12 percent). The intervention codings were aggregated to create two categories: a meaning emphasis (mixed, comprehension, vocabulary, metacognition, and independent reading) and code emphasis (word recognition, phonemic awareness, and fluency). Of the 20 studies, 15 were categorized as meaning emphasis, with only 1 clearly as code emphasis, and 3 categorized as other.

Analysis of Effect Sizes

The effect sizes (using the Hedges g correction for sample size) for all 89 outcomes are reported in Appendix F and summarized (as averages weighted for the number of effect sizes in each study) in Table 2 for the 20 studies that survived all three screens.
<table>
<thead>
<tr>
<th>Study</th>
<th>Number of Effects</th>
<th>Hedges' g</th>
<th>Standard error</th>
<th>Variance</th>
<th>Lower limit</th>
<th>Upper limit</th>
<th>Z-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alfassi</td>
<td>3</td>
<td>0.815</td>
<td>0.352</td>
<td>0.124</td>
<td>0.125</td>
<td>1.506</td>
<td>2.314*</td>
</tr>
<tr>
<td>Dalton</td>
<td>1</td>
<td>0.424</td>
<td>0.204</td>
<td>0.042</td>
<td>0.023</td>
<td>0.825</td>
<td>2.075*</td>
</tr>
<tr>
<td>Gentry</td>
<td>3</td>
<td>0.135</td>
<td>0.279</td>
<td>0.078</td>
<td>-0.412</td>
<td>0.682</td>
<td>0.483</td>
</tr>
<tr>
<td>Fasting</td>
<td>6</td>
<td>0.584</td>
<td>0.284</td>
<td>0.080</td>
<td>0.028</td>
<td>1.140</td>
<td>2.059*</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>4</td>
<td>0.521</td>
<td>0.181</td>
<td>0.033</td>
<td>0.166</td>
<td>0.875</td>
<td>2.876**</td>
</tr>
<tr>
<td>Henao</td>
<td>4</td>
<td>0.668</td>
<td>0.451</td>
<td>0.203</td>
<td>-0.215</td>
<td>1.552</td>
<td>1.483</td>
</tr>
<tr>
<td>Higgins</td>
<td>1</td>
<td>0.600</td>
<td>0.261</td>
<td>0.068</td>
<td>0.089</td>
<td>1.111</td>
<td>2.301*</td>
</tr>
<tr>
<td>Jones</td>
<td>10</td>
<td>0.334</td>
<td>0.193</td>
<td>0.037</td>
<td>-0.044</td>
<td>0.712</td>
<td>1.731</td>
</tr>
<tr>
<td>Kramarski</td>
<td>3</td>
<td>-0.204</td>
<td>0.283</td>
<td>0.080</td>
<td>-0.758</td>
<td>0.350</td>
<td>-0.721</td>
</tr>
<tr>
<td>Leu</td>
<td>6</td>
<td>0.503</td>
<td>0.303</td>
<td>0.092</td>
<td>-0.090</td>
<td>1.097</td>
<td>1.662</td>
</tr>
<tr>
<td>Ligas</td>
<td>8</td>
<td>0.029</td>
<td>0.093</td>
<td>0.009</td>
<td>-0.153</td>
<td>0.210</td>
<td>0.312</td>
</tr>
<tr>
<td>Liu</td>
<td>3</td>
<td>2.679</td>
<td>0.361</td>
<td>0.130</td>
<td>1.971</td>
<td>3.387</td>
<td>7.420**</td>
</tr>
<tr>
<td>Reinking88</td>
<td>12</td>
<td>0.214</td>
<td>0.251</td>
<td>0.063</td>
<td>-0.278</td>
<td>0.706</td>
<td>0.852</td>
</tr>
<tr>
<td>Reinking90</td>
<td>7</td>
<td>0.691</td>
<td>0.371</td>
<td>0.138</td>
<td>-0.036</td>
<td>1.419</td>
<td>1.863</td>
</tr>
<tr>
<td>Rouse</td>
<td>4</td>
<td>0.060</td>
<td>0.136</td>
<td>0.018</td>
<td>-0.206</td>
<td>0.326</td>
<td>0.442</td>
</tr>
<tr>
<td>Solomon</td>
<td>4</td>
<td>1.563</td>
<td>0.321</td>
<td>0.103</td>
<td>0.933</td>
<td>2.192</td>
<td>4.862**</td>
</tr>
<tr>
<td>Solan</td>
<td>1</td>
<td>0.664</td>
<td>0.365</td>
<td>0.134</td>
<td>-0.053</td>
<td>1.380</td>
<td>1.816</td>
</tr>
<tr>
<td>Underwood</td>
<td>1</td>
<td>-0.027</td>
<td>0.174</td>
<td>0.030</td>
<td>-0.367</td>
<td>0.314</td>
<td>-0.153</td>
</tr>
<tr>
<td>Vollands</td>
<td>6</td>
<td>0.374</td>
<td>0.388</td>
<td>0.150</td>
<td>-0.386</td>
<td>1.134</td>
<td>0.965</td>
</tr>
<tr>
<td>Xin</td>
<td>6</td>
<td>0.264</td>
<td>0.229</td>
<td>0.052</td>
<td>-0.184</td>
<td>0.712</td>
<td>1.155</td>
</tr>
<tr>
<td>Random</td>
<td>Total of 89 effect sizes</td>
<td>0.489</td>
<td>0.112</td>
<td>0.013</td>
<td>0.269</td>
<td>0.709</td>
<td>4.360**</td>
</tr>
</tbody>
</table>

= p<.05, **=p<.01
As reported in Table 2, within a random effects model (Lipsey & Wilson, 2002), the weighted mean of these 89 corrected effect sizes is 0.49 \((sd=0.74) (z=4.36, p<0.0005)\). All 89 effect sizes, along with the 95 percent confidence intervals are portrayed graphically in Figure 1. The forest plot provides a simple visual representation of the amount of information and variation from the individual studies that are part of this meta-analysis (with the weighted mean effect size appearing as the the right most entry). In the plot, the weighted average (Hedges g) of all effect sizes for each study are shown as a vertical line with a diamond plus two tiny rectangles; the diamond is weighted effect size and the two small rectangles indicate the limits of the 95 percent confidence interval for the effect sizes in any particular study.

![Figure 1. Forest Plot of the Combined Effect Sizes for the 20 Studies](image)

**Meta Analysis of Literacy and Technology in the Middle Grades**

<table>
<thead>
<tr>
<th>Study</th>
<th>Comparison</th>
<th>Hedges's g &amp; 95% CI</th>
<th>Relative weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alfassi</td>
<td>Combined</td>
<td></td>
<td>4.17</td>
</tr>
<tr>
<td>Dalton</td>
<td>Read</td>
<td></td>
<td>5.74</td>
</tr>
<tr>
<td>Gentry</td>
<td>Combined</td>
<td></td>
<td>4.93</td>
</tr>
<tr>
<td>Fasting</td>
<td>Combined</td>
<td></td>
<td>4.88</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>Combined</td>
<td></td>
<td>5.99</td>
</tr>
<tr>
<td>Henao</td>
<td>Combined</td>
<td></td>
<td>3.31</td>
</tr>
<tr>
<td>Higgs</td>
<td>Combined</td>
<td></td>
<td>5.13</td>
</tr>
<tr>
<td>Jones</td>
<td>Combined</td>
<td></td>
<td>5.86</td>
</tr>
<tr>
<td>Kramarski</td>
<td>Combined</td>
<td></td>
<td>4.89</td>
</tr>
<tr>
<td>Leu</td>
<td>Combined</td>
<td></td>
<td>4.68</td>
</tr>
<tr>
<td>Ligas</td>
<td>Combined</td>
<td></td>
<td>6.77</td>
</tr>
<tr>
<td>Liu</td>
<td>Combined</td>
<td></td>
<td>4.09</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>Combined</td>
<td></td>
<td>5.23</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Combined</td>
<td></td>
<td>3.99</td>
</tr>
<tr>
<td>Rouse</td>
<td>Combined</td>
<td></td>
<td>6.43</td>
</tr>
<tr>
<td>Salomon</td>
<td>Combined</td>
<td></td>
<td>4.48</td>
</tr>
<tr>
<td>Solan</td>
<td>TechnoRead</td>
<td></td>
<td>4.05</td>
</tr>
<tr>
<td>Underwood</td>
<td>ILS</td>
<td></td>
<td>6.06</td>
</tr>
<tr>
<td>Vollands</td>
<td>Combined</td>
<td></td>
<td>3.84</td>
</tr>
<tr>
<td>Xin</td>
<td>Combined</td>
<td></td>
<td>5.48</td>
</tr>
</tbody>
</table>

**Random Effects Model**

On the basis of the overall mean weighted effect size, one can and should conclude that the range of digital technologies used to ameliorate the reading performance of middle-school students is quite effective; in terms of the norms for meta-analysis (Cohen, 1988), this would qualify as a “moderate” overall effect size 0.5–0.8). When examined as percentages, of the 89 effect sizes calculated, 26 percent were large (>0.8), 32 percent were moderate (0.5–0.8), and 42 percent were “small” or lower (0.01–0.5). The key term here is range, for there are many types of interventions, and clearly some are not any more effective than garden-variety print-oriented instruction while others produce sizable advantages over conventional approaches.
Examining Simple Effects Within Categories

Of particular interest for our purposes are a set of very specific comparisons related to the variations in programmatic, assessment, and contextual variables. For example, for the 57 effect sizes reported for a general, undifferentiated population of middle school students, the mean effect size was 0.52, whereas the effect size for targeted populations of students (e.g., students classified as possessing learning disabilities or as struggling readers) was 0.32 (N_{es} =29); this was a statistically reliable difference, Q=4.42, p<0.05. In comparing meaning focused interventions (the combination of mixed, comprehension, vocabulary, and metacognition) with those that were code focused (the combination of phonics, phonemic awareness and fluency), we found no mean effect size difference favoring one emphasis over another, Q=1.82, p>0.05. The mean weighted effect size among studies emphasizing meaning was 0.43 (N_{es}=70) compared to 0.20 for code (N_{es}=12)

Study duration, we reasoned, was important, due to the common observation among intervention studies that pedagogical experiments often fail to show effects because the intervention does not have time to “take hold.” Our results did not confirm the “longer is better” conventional wisdom; we instead found a “U-shaped” distribution of effects that, while provocative, was not statistically reliable, Q=2.23, p<0.33: Effect sizes in studies lasting two to four weeks (N_{es}=21, ES=0.55) were larger than those in studies lasting less than a week (N_{es}=25, ES=0.48) but much larger than those from studies lasting five or more weeks (N_{es}=43, ES=0.34).

Sample size was a robust predictor of effect size; small n studies (30 or less) produced 14 effect sizes averaging 0.77, while large n (31 or more) studies produced 75 effect sizes with a mean of 0.38, Q=3.24, p<0.20. The possibility exists that the loss of control that comes from larger scale implementation of interventions, especially when they are implemented for longer periods of time, may result in a loss of power and precision; this is certainly a plausible hypothesis for a larger meta-analysis encompassing many other subject areas and target populations.

Whether a study controlled for pretest equivalency through random assignment (N_{es}=44, ES=0.42) or some sort of pretest covariate (N_{es}=45, ES=0.45) did not account for a significant amount of variation in effect sizes, Q=.16, p<.69. Type of test revealed substantial and statistically significant differences in effect size, Q=18.62, p<0.01. Tests produced by test companies, largely standardized measures (N_{es}=41, ES=0.30), were less sensitive to treatment effects than experimenter-designed assessments (N_{es}=34, ES=0.56). Other (a catchall category) tests produced an effect size of 1.05, but there were so few effect sizes (N_{es}=3) that little credence can be given to that estimate.

We also examined effect sizes by their "policy focus," categorizing studies according to whether their primary purpose was to (a) reduce the achievement gap, (b) increase technology use in general, or (c) improve a specific educational outcome, such as reading comprehension. We found no statistically unreliable differences, Q=1.68, p>0.05. For the 25 effect sizes coming from studies designed to improve the achievement gap, the mean effect size was 0.55, where as the mean effect size for the studies (N_{es}=30) designed to increase general technology use was 0.36.
The mean effect size for the studies (N\textsubscript{es}=34) designed to improve a specific educational outcome as 0.41.

Another variable of interest is what we dubbed technology source, for lack of a more precise label. It contrasts whether the technology originates with a commercial source (e.g., programs such as Fast Forward or Accelerated Reader), the researcher’s personal vision of what a technological learning environment ought to look like (e.g., Hasselbring & Goin, 2004), or a well-studied “delivery system,” such as electronic text with a dictionary available for word pronunciation and meaning. When we grouped studies on that variable, the differences were quite compelling and statistically significant, $Q=32.19$, $p<0.0001$. The 34 effect sizes from the commercial studies yielded a mean weighted effect size of 0.28, while the 44 effect sizes from delivery system studies averaged 0.34, and the 11 effect sizes from researcher-designed interventions came in at an effect size of 1.20. There appears to be something special about those “tailored” systems designed by individual research teams for specific purposes.

While it was not central to our investigation, we were interested in whether publication venue was a reliable predictor of effect size. So we compared publication in technology journals (N\textsubscript{es}=25, ES=0.54) with literacy journals ($n=30$, ES=0.36) with broader educational journals (N\textsubscript{es}=34, ES=0.41). This difference was not statistically reliable, $Q=.1.73$, $p>0.05$.

For convenience, these comparisons are summarized below in Table 3.

<table>
<thead>
<tr>
<th>Table 3. Summary of Effects Between Levels of Relevant Variables—Random Effects Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Moderator Variable: Levels</td>
</tr>
<tr>
<td>Student Sample Size:</td>
</tr>
<tr>
<td>30 or less</td>
</tr>
<tr>
<td>31 or more</td>
</tr>
<tr>
<td>Focus of intervention:</td>
</tr>
<tr>
<td>Code</td>
</tr>
<tr>
<td>Meaning</td>
</tr>
<tr>
<td>Type of test:</td>
</tr>
<tr>
<td>Test Co.</td>
</tr>
<tr>
<td>Res Dev</td>
</tr>
<tr>
<td>Other</td>
</tr>
<tr>
<td>Country</td>
</tr>
<tr>
<td>USA</td>
</tr>
<tr>
<td>World</td>
</tr>
<tr>
<td>Moderator Variable: Levels</td>
</tr>
<tr>
<td>---------------------------</td>
</tr>
<tr>
<td>Duration of Study:</td>
</tr>
<tr>
<td>&lt;1 week</td>
</tr>
<tr>
<td>2–4 weeks</td>
</tr>
<tr>
<td>5 weeks +</td>
</tr>
<tr>
<td>Pretest Equivalency:</td>
</tr>
<tr>
<td>Rdm Asnt</td>
</tr>
<tr>
<td>Others</td>
</tr>
<tr>
<td>Publication Type:</td>
</tr>
<tr>
<td>Tech</td>
</tr>
<tr>
<td>Reading</td>
</tr>
<tr>
<td>Other</td>
</tr>
<tr>
<td>Focus of Policy:</td>
</tr>
<tr>
<td>↓ Ach Gap</td>
</tr>
<tr>
<td>↑ Techn</td>
</tr>
<tr>
<td>Oth Outc</td>
</tr>
<tr>
<td>Target Population:</td>
</tr>
<tr>
<td>GenEd</td>
</tr>
<tr>
<td>Other</td>
</tr>
<tr>
<td>Tech Source:</td>
</tr>
<tr>
<td>Commercial</td>
</tr>
<tr>
<td>Delivery</td>
</tr>
<tr>
<td>ResDev</td>
</tr>
<tr>
<td>Experimental Design:</td>
</tr>
<tr>
<td>Independent Groups</td>
</tr>
<tr>
<td>Correlated</td>
</tr>
</tbody>
</table>

<sup>a</sup>: Q values with p<0.05 indicate that effect sizes differ significantly across levels of the moderator variable. *p < 0.05; **p < 0.01

**Summary of Results**

This meta-analysis suggests a number of findings relevant to those interested in the use of technology to improve literacy acquisition and instruction at the middle-school level.

1. As was highlighted by others, very little experimental research exists in this domain. The research that does exist focuses mainly on reading comprehension, with a little emphasis on metacognitive performances but virtually no attention to issues of motivation and
engagement. This is all the more surprising given the common claims about the motivational value of technology.

2. A wide range of digital technologies appears to enhance the reading performance of middle school students as evidenced by the robust overall effect size obtained in this meta-analysis.

3. A number of specific outcomes merit our attention as a field:

   a. The effect sizes were greater for interventions aimed at general populations than those with specific needs (i.e. students who are learning disabled or struggling readers). We can only speculate about why this might be the case, and we surely need more evidence before reaching a definitive conclusion. However, issues of engagement and appropriate levels of support and feedback suggest themselves as reasonable explanations.

   b. Standardized measures from test companies were less sensitive to treatment effects than researcher-developed measures in several of the studies in this meta-analysis.

   c. Studies with smaller sample sizes were much more likely to achieve substantial effects than those with larger sample sizes. This counter-intuitive finding is puzzling because of what we know about the increase in statistical power that comes with larger experimental samples. On the other hand, there may be a trade-off between statistical power and experimental precision; that is, it may be easier for researchers to maintain a high degree of fidelity to treatment in smaller studies because of the greater manageability prospects.

   d. Technologies that were created by a research team had a much larger effect size than those technologies either adapted from the commercial market or those that merely used the technology as a delivery system. In addition, those created by researchers tended to have a clear theoretical focus that was matched by the assessments employed by the team.

   e. Studies that used some sort of correlated design (pretests used as covariates for posttest or repeated measures designs in which the same subjects cycle through different interventions) are more likely to find reliable differences between interventions that an independent group designs.
Suggestions for Policy and Practice

We undertook this meta-analysis to determine the state of research-based knowledge about the role of technology in improving reading performance in the middle-school grades. Of particular importance were digital technologies to improve five areas of literacy acquisition: independent strategy use, meta-cognition, reading motivation, reading engagement, and reading comprehension. Unfortunately, we were able to locate studies addressing primarily reading comprehension and vocabulary, with three studies investigating phonological aspects of reading.

As we already suggested, this is a grave concern given the hope we collectively express for the motivation and engagement that technology ought to promote among learners, particularly learners who have not experienced success with conventional curricular tools. That said, the research we did locate is encouraging for it shows that these digital learning environments and tools can impact learning. These findings have some implications for curricular practice and for research.

Recommendations for Practice

1. *The overall positive impact of technology environments, especially on comprehension outcomes, should prompt us to feel comfortable in recommending broader implementation of programs that have undergone careful evaluations of their effects on student learning.* Even though we are tempted to say that educators should consider the adoption of programs that possess the same features as those shown to be effective in this analysis (e.g., focus on meaning, using a mixed set of technology tools), we think it safer for consumers to require careful evaluation of any specific technology program before recommending widespread adoption.

   Moreover, the relatively modest impact of commercial programs should prompt us to adopt a highly skeptical stance toward claims made by individual vendors and redouble our insistence on high quality, independent evaluations of commercial products prior to adoption. (In an earlier era, the Educational Products Information Exchange [EPIE] served as a kind of *Consumer Reports* for educational products. With the proliferation of software packages and hardware tools, it is needed now more than ever. Perhaps the What Works Clearinghouse can serve such a function.)

2. *Program adoption for populations of struggling readers requires even more careful evaluation.* Our data analyses suggest that positive outcomes for struggling readers are much harder to come by. Given the focus of current policy on interventions for struggling readers, students with learning disabilities, and other special populations, we believe it would be unwise to adopt a program that had not shown an effect for a specific target population. We also believe, and explicitly suggest, that much greater emphasis on research on tools designed especially for struggling readers is needed.

3. *Current reading assessments, especially commercial assessments, do not appear sensitive to the interventions possible through technology.* Somewhat commercial assessments do not capture what these interventions are all about, and we believe, as we suggest below in...
Recommendations for Future Research

As we consider future research in this area, we believe that the following recommendations deserve our collective consideration and action:

1. The present data reinforce the many existing calls for more research in this area. If one puts together three key findings from this meta-analysis [(a) there are not enough experimental studies, (b) there is a narrow focus on cognitive outcomes (comprehension), and (c) the existing studies show promising effects on literacy acquisition], one is led to the conclusion that we should continue, perhaps even expand, funding for research on technological interventions to improve literacy acquisition at the middle-school level. As promising as it is, there is just too little research to allow for us to make strong claims about the efficacy of technology on literacy.

After multiple filtering phases to ensure the correct population, the appropriate intervention, and rigorous research, only 20 studies survived. As such, only one of the five initial research questions could be answered. Funding for future research should move beyond existence proofs (technology can make a difference) to provide more specific and nuanced information about when, where, why and how technology can support teaching and learning for middle school literacy acquisition. Our call for research echoes the concerns and needed directions expressed by leading authors in literacy and technology (e.g., Labbo & Reinking, 1999; Leu, in press).

2. Future research may need to balance issues of focus against standards of control and precision. The largest effect sizes in this meta-analysis were from studies used a smaller n; moreover, there is a tendency, albeit nonsignificant for shorter studies to produce greater effects. This suggests that research studies that last too long might be open to maturation effects or other confounding variables. Research that takes place too quickly might not provide time for the intervention to take hold. Studies with large sample sizes might compromise researcher control that would be available in a smaller, more manageable study.

The larger issue implied by this recommendation is the question of what research methods ought to be employed in the conduct of research in this or any other educational arena. Complementarity, it seems to us, is called for in this arena. The complementarity principle would suggest that in any venture, we begin with small-scale descriptive studies before moving on to more careful design or formative experiments that help us narrow the range of relevant variables in anticipation of carefully controlled randomized experiments and, finally, studies of what happens in the scaling up process. This principle
seems even more important in a relatively new field, such as the development of digital tools to enhance literacy learning.

3. **As a field, we should develop a master codebook that could serve the research community as a heuristic for analyzing digital technologies and their impact on literacy acquisition in the middle-school grades (perhaps beyond).** This recommendation originated in the work of Cavanaugh et al. (2004), and its utility was once again demonstrated in this meta-analysis. There are many complexities related to studying digital tools and their impact on literacy acquisition; a research field without such a heuristic will find it difficult to compare outcomes or to come to any concrete conclusions about implications for teaching literacy at this level. We found the Waxman system (see Table 1 and Appendix E), with a few tweaks to make it more literacy-centric, to be quite useful to us, and we would recommend it to others.

4. **Future research needs to examine the relation between commercial products and researcher-developed technology interventions.** Little research has investigated commercial technology products used for improving literacy acquisition at the middle-school level. However, this meta-analysis has provided evidence that researcher-developed technologies seem to be more effective than their commercial counterparts. This finding could be due to the fact that in several of the studies in our corpus the researchers also developed the measures used to determine the effectiveness of the program. As such, the measures may be “testing the tool” rather than striving for transfer.

It is also possible that by working together researchers, educators, and technologists are better able to create a system tailored specifically to meet the needs of particular audiences than commercial products trying to serve large audiences. As we will argue later, stronger, more valid and more reliable measures (along with a better coding heuristic) will help address this issue of whether the difference between commercial programs is an artifact of the match between assessments and programs or a result of more careful implementation of a learning environment. If it is the case that researchers are better able to develop effective literacy tools, then better dissemination plans need to be enacted to share these benefits with practitioners—and possibly with the educational publishing community, so that they can infuse promising new technological innovations into their products.

Two other recommendations for research are only indirectly implied—and certainly not licensed—by our meta-analysis, but both are worth mentioning because they are so central to the future of research in this area.

1. **Assessment.** Our meta-analysis did unearth assessment, especially the question of what sorts of assessments should count as evidence of the efficacy of a technological intervention, as an issue. We believe that the research on digital tools for middle school literacy acquisition should include a focus on developing measures to evaluate outcomes that are generalizable, comparable, and replicable.

   We found that researcher-developed measures yielded greater effect sizes than external standardized tests. Is it because these highly curricular-embedded, researcher-developed tests are more relevant to the treatment and hence more valid—
or just a reflection of what happens when a program teaches to the test and in the process compromises the generalizability of the intervention, compared to what might have been achieved with standardized measures? We are not sure, but we are sure that the issue needs our scholarly attention.

2. **Engaging teachers in technology interventions.** Few would argue with the assertion that teachers need practical information to learn how to best use digital tools in the classroom. As a research field, we are still a long way from helping teachers implement effective classroom technology systems. Thus, we would welcome research on how to assist teachers in implementing technology. However, more is needed. Most of the interventions in our analysis put the researcher at the center of the classroom implementation of the technology and positioned the teacher as a bystander.

We would like to see collaborative research that engages teachers from the outset in the design and implementation of classroom digital tools. Only when researchers engage teachers from the conceptualization of their technology tools can researchers benefit from the wisdom of teaching in their designs. Only when researchers expand their methodological repertoire to include iterative design experiments in advance of randomized field trials will there be a place for teachers to engage in full and continuous collaboration.

Finally, a comment for those who would raise the issue of whether it is worth doing a meta-analysis on a corpus of only 20 studies: There appears to be a general belief among some educational researchers that a large number of studies must be included in a meta-analysis project in order to draw substantive conclusions. For example, the National Reading Panel on Technology (NRP, 2000) decided not do a meta-analysis because there were only 21 studies identified. Given the wider range of grades and questions asked in that initiative, perhaps the number of studies would not have been sufficient. However, even in that effort, we should note that even though no meta-analysis was carried out, the NRP found that all 21 studies indicated the positive effects of technology on reading performance and reached positive conclusions about its efficacy.

By focusing on an undefined and statistically unsupported assumption about a minimum number of studies to carry out a meta-analysis the more relevant concept of heterogeneity is obscured. Heterogeneity refers to the fact that studies grouped together in a systematic review will differ in a variety of systematic and random ways. The differences can be in experimental design, outcomes measures reported, and other factors. Statistically, heterogeneity means that observed treatment effects differ more from each other than one would expect from random factors alone. Thus the more important task to carry out in meta-analysis is to more precisely abstract useful and homogeneous information from the studies and manipulations of the specific construct(s) of interest.

Hardy and Thompson (1998) examined various factors that impact the power of a heterogeneity test. They included such factors as the number of studies, the total information available, and the distribution of weights. Their findings show that the power increases with the total amount of information not merely the numbers of studies in a meta-analysis. Hardy and Thompson also
showed that if a particular study contributes an inordinately large amount to the overall weighted mean effect size, the power is substantially lowered.

Given two important facts—(1) that this meta-analysis had a very specific focus of (reading and technology in Grades 6–8) and (2) that our admittedly small number of studies provided a large amount of information about the effects of technology on reading—we can be more confident about our findings and conclusions. Granted, our meta-analysis would be stronger if there were many more experiments available, but we believe we have made a solid beginning in looking at technology and reading.

We also note that no single study in our meta-analysis overwhelmed the other studies in terms of contributions to the overall weighted mean (this can be seen by examining the column of relative weight on the forest plot in Figure 1). Hardy and Thompson (1998) conclude their article by pointing out that that expert judgment deserves as much weight as statistical analyses of heterogeneity in determining weight and significance.

Our confidence in recommending more policy and research attention to technology, thankfully, is supported by the dual criteria of statistical scrutiny and wisdom. We believe the time has come to take technology more seriously as a component of middle-school literacy curriculum and pedagogy.
References

References marked with an asterisk indicate studies used in this meta-analysis.


Schacter, J. (2001). The impact of education technology on student achievement: What the most current research has to say. Santa Monica, CA: Milken Exchange on Education Technology.


Appendix A
Keywords Used for Web Searches

adolescent
achievement
cognitive
computer
computer-based instruction
comprehension
digital media
educational technology
electronic media
evaluation
experiment
hypermedia
hypertext
instruction
Internet
intervention
language
learning
learning environment
metacognition
middle school
middle grades
multimedia
online
open learning
quantitative
quasi-experimental
phonemic awareness
pretest, posttest
print
randomized
reading
research
strategy
technology
textbook
validity
vocabulary
web-based
6th grade (or sixth grade)
7th grade (or seventh grade)
8th grade (or eighth grade)
Appendix B
Academic and Educational Databases

Blackwell Science Synergy
Directory of Open Access Journals
Ebsco Research Databases
ERIC
Gale Group Databases
JSTOR
Ingenta Select
Kluwer
Lawrence Erlbaum Journals
MetaPress
OCLC FirstSearch – Periodical Abstracts
Ovid
ProQuest Education
PsychInfo
PubMed
Sage Publications
SpringerLink
Wiley Interscience
Wilson Education.
Appendix C
Educational Technology and Reading Journals

American Educational Research Journal
American Journal of Distance Education
American Annals of the Deaf
Association for the Advancement of Computing in Education
Behavior Research Methods, Computers and Instrumentation
Children’s Literature in Education
Communication Disorders Quarterly
Computer Science Education
Computers in Human Behavior
Computers in the School
Computers & Education
Contemporary Educational Psychology
Disability and Rehabilitation
Distance Education
Economics of Education Review
Education and Information Technologies
Education Policy Analysis Archives
Educational Psychology
Educational Psychologist
Educational Technology & Society
Educational Technology Research and Development
Electronic Journal for the Integration of Technology in Education
Elementary School Journal
E-learning
E-Learning and Education
Human and Computer Interaction
Human Factors
Information Technology, Learning and Performance
Interactive Learning Environments
Journal of Asynchronous Learning Networks
Journal of Adolescent and Adult Literacy
Journal of Applied Psychology
Journal of Computer Assisted Learning
Journal of Computer Mediated Communication
Journal of Computers in Math and Science Teaching
Journal of Computing in Childhood Education
Journal of Distance Education
Journal of Distance Learning
Journal of Education Technology Systems
Journal of Educational Computing Research
Journal of Educational Computing, Design & Telecommunications
Journal of Educational Media
Journal of Educational Psychology
Journal of Educational Research
Journal of Educational Technology Research and Development
Journal of Experimental Child Psychology
Journal of Experimental Psychology
Journal of Information Technology Education
Journal of Interactive Media in Education
Journal of Interactive Learning Research
Journal of Interactive Online Learning
Journal of Learning Disabilities
Journal of Literacy Research
Journal of Reading Behavior
Journal of Research in English
Journal of Research on Technology in Education
Journal of Teaching, Learning and Assessment
Journal of Technology Education
Journal of Technology Studies
Journal of the Learning Sciences
Language, Learning, and Technology
Language and Leading with Technology
Learning Disabilities: Research and Practice
Learning and Instruction
Learning and Leading with Technology
Journal of Special Education Technology
Open Education
Reading Online
Reading Psychology
Reading Research and Instruction
Reading Research Quarterly
Reading and Writing
Reading and Writing Quarterly
Research in Education Education
Scientific Studies of Reading
Technology and Learning
TechKnowLogia: International Journal of Technologies for the Advancement of Knowledge and Learning
The Reading Matrix.
Appendix D
International Journals

Australian Educational Computing
Australian Journal of Education
Australian Journal of Educational and Developmental Psychology
Australian Journal of Educational Technology
Australian Journal of Language and Literacy
Australasian Journal of Educational Technology
British Educational Research Journal
British Journal of Educational Psychology
British Journal of Educational Technology
British Journal of Learning Disabilities
British Journal of Special Needs Education
Canadian Journal of Education
Canadian Journal of Educational Communication
Canadian Journal of Experimental Psychology
Canadian Journal of Learning and Technology
Enseñanza de las Ciencias
European Education
European Journal of Cognitive Psychology
European Journal of Education
European Journal of Psychology of Education
European Journal of Special Needs Education
Infancia y Aprendizaje
International Journal of Artificial Intelligence in Education
International Journal of Educational Technology
International Journal on E-learning
International Review of Research in Open and Distance Learning
Language & Literacy: A Canadian Educational e-journal
Oxford Review of Education
Revista de Ciencias Humanas
Revista Electronica de Investigacion Educativa
Revista Iberoamericana de Educacion
Turkish Online Journal of Distance Education
Scandinavian Journal of Educational Research
Scandinavian Journal of Psychology
Appendix E

Meta-Analysis Coding for Reading and Technology Studies
(Revised from Waxman, 2003)

1. Study Characteristics
   a. Author (Report last name, first; e.g., Doe, John).
   b. Year of Study (Report year of study; e.g., 2000).
   c. Number of Comparisons Within Study (Report number; e.g., 1 or 2 or 3).
   d. Student Sex (Males = 1; Females = 2; Mixed or not specified = 3).
   e. Grade Level (Unspecified = 0; on target (6–8th grade)=1; on target + below=2; on target + above=3; on target plus above and below=4; Just below=5; just above=6; other=9)
   f. Unit of Analysis (Unspecified = 0; Individual = 1; Class = 2; School = 3; District = 4; State = 5; Mixed = 6).
   g. Student Sample Size (Report actual sample size of both groups; e.g., 4,024).
   h. School Sample Size (Report actual sample size; e.g., 4,024).
   i. Publication Features (Technology journal = 1; Reading or Literacy journal = 2; Special Education=3, Other educational journal = 4; not in archival literature = 5).
   j. Target Population (Unspecified=0; General Ed=1; Special Education=2; Struggling Readers=3; Language ESL in USA=4; Language ESL in Other Country=5; Other second language learning=6; Other=9).
   k. Students’ Ethnicity (Unspecified = 0; Black = 2; Hispanic = 3; Asian = 4; White = 5; Mixed = 6; Other = 9).
   l. Students’ Socioeconomic Status (Unspecified = 0; Lower = 1; Lower middle = 2; Middle = 3; Upper middle = 4; Upper = 5; Mixed = 6).
   m. Country (Unspecified = 0; USA = 1; Canada = 2; Mexico/Latin America = 3; Europe = 4; Asia = 5; South America = 6; Cross-Cultural = 7; Middle East = 8; Other=9)
   n. Geographical Region (if in USA) (Northeast = 1; Southeast = 2; Midwest = 3; South Central = 4; Southwest = 5; Northwest = 6; Mixed = 7; Other = 9).
   o. School Type (Unspecified = 0; Public = 1; Private = 2; Special school = 3; Mixed = 4; Other = 9).
   p. Community Type (Unspecified = 0; Urban = 1; Rural = 2; Suburban = 3; Mixed = 4; Other = 9).
   q. Content Area (Content area where reading technology is used. Unspecified = 0; Technology = 1; Reading = 2; Mathematics = 3; Social studies = 4; Science = 5; Reading and math = 6; Language arts = 7; Foreign language = 8; Mixed = 9; Other = 10).

2. Quality of Study Indicators
   a. Method of Observation of Independent Variable (i.e., how was the technology intervention documented—how did they look to see if the kids did it).
      Unspecified = 0; Systematic observation = 1; Informal observation = 2; Student survey or interview = 3; Teacher survey or interview = 3; Administrator survey or interview = 4; Computer logs = 5; Multiple methods = 6; Other = 9).
b. Pretest Equivalency (Has the initial differences between the two groups been accounted for? Unspecified = 0; Statistical Control (e.g., ANCOVA, regression) = 1; Random Assignment = 2; Statistical Control and Random Assignment = 3; Gain Scores = 4; Matching = 5; Other = 9).

c. Name of test or measure (report actual name)

d. Reported Reliability of Measures (Unspecified = 0; Actual reliability statistic (e.g., 70 or 83).

e. Manner in Which Outcome Scores Are Reported (Unspecified = 0; Standard scores = 1; Raw scores = 2; Percentile ranks = 3; Gain scores = 4; Residualized Posttest scores = 5; Other=9).

f. Duration of Study (Unspecified = 00; List the number of weeks that the implementation of the technology occurred).

g. Cognitive Outcomes (Unspecified = 0; Testing company standardized achievement test = 1; Federal/national standardized test = 2; State-level achievement test = 3; District-level achievement test = 4; School-level test = 5; Teacher-made test = 6; Researcher-developed test = 7; Test developed by other researchers=8; Authentic assessment = 9; Creativity test = 10; Higher-level thinking test = 11; Other = 19).

h. Affective Outcomes (Unspecified = 0; Student attitudes toward computers = 1; student attitudes toward reading = 2; student attitudes other = 3; Academic self-concept or motivation = 4; student preference for electronic media = 5; Other = 19).

i. Behavioral Outcomes (Unspecified = 0; Student time-on-task = 1; student perseverance = 2; Tasks attempted = 3; Tasks completed = 3; Success rate = 4; Positive peer interaction = 5; Interactivity with computers = 6; Other = 9).

j. Effect Size Coefficient (actual coefficient)

k. Statistics (Statistics used in determining effect size; Means = 1; t-value = 2; F-value = 3; Chi-square = 4; Mixed = 5; Anova=6; Other=9).

l. Weight (One divided by the actual number of comparisons in the study, e.g., 3 comparisons = 1/3 or .333).

3. Sources of Invalidity

a. Type of Design (Quasi-experimental/nonrandomized one group pretest-posttest = 1; Nonrandomized static-group comparison = 2; Nonrandomized pre-post control group = 3; Time series = 4; Randomized posttest-only control group = 5; Randomized pre-post control group = 6; Repeated Measures = 7; Other=9).

b. History (Have specific events occurred between the first and second measurement in addition to the experimental variable? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

c. Maturation (Are there processes within the participants operating as a function of the passage of time [e.g., growing older, more tired] that might account for changes in the dependent measure? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).
d. Testing (Is there an effect of taking a test upon the scores of a second testing? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

e. Instrumentation (Do changes in calibration or observers’ scores produce changes in the obtained measurement? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

f. Statistical Regression (Have groups been selected on the basis of their extreme scores? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

g. Selection Bias (Have biases resulted in the differential selection of comparison groups? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

h. Mortality (Has there been a differential loss of participants from the experimental and control groups? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

i. Selection-Maturation Interaction (Is there an interaction between extraneous factors such as history, maturation, or testing and the specific selection differences that distinguish the experimental and control groups? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

j. Reactive or Interaction Effect of Testing (Does pretesting influence the participants’ responsiveness to the experimental variable, making the results for a pretested population unrepresentative of the effects of the experimental variable for the unpretested universe from which the participants were selected? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

k. Interaction of Selection Biases and Treatment (Are there selective factors upon which sampling was based which interact differentially with the experimental variable? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

l. Reactive Effects of Experimental Arrangements (Are there effects of the experimental setting that would preclude generalizing about the effect of the experimental variable upon persons being exposed to it in nonexperimental settings? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

m. Multiple-Treatment Interference (Are there nonerasable effects of previous treatments applied to the same participants? Adequately controlled by design = 1; Definite weakness of design = 2; Possible source of concern = 3; Not a relevant factor = 4).

n. Statistical Power (Is the sample size large enough to reject the null hypothesis at a given level of probability, or are the estimate coefficients within reasonably small margins of error? i.e. each group has how many) [a sample > 60 for groups such as classes, schools, or districts; a sample >100 for individuals]. Probable threat [< 60 for groups or < 100 for individuals as the unit of analysis] = 1; Adequately minimized [> 60 for groups; > 100 for individuals] = 2).
4. Reading Characteristics
   a. The Focus of the intervention (what they did)
      • 1 = Phonics
      • 2 = Phonemic awareness
      • 3 = Vocabulary
      • 4 = Reading comprehension
      • 5 = Fluency
      • 6 = independent reading
      • 7 = Mixed
      • 8 = Meta-cognition
      • 9 = Content Learning
      • 19 = Other
   b. The focus of the outcome measures (what they observed)
      • 1 = phonics
      • 2 = phonemic awareness
      • 3 = vocabulary
      • 4 = reading comprehension
      • 5 = fluency
      • 6 = reading volume
      • 7 = reader response (response to literature)
      • 8 = Spelling
      • 9 = Word Recognition
      • 10 = Aggregate
      • 11 = Meta-cognition
      • 12 = Motivation
      • 19 = Other

5. Technology Characteristics
   a. Type of Technology (Unspecified = 0; PCs = 1; Laptops = 2; Networked labs = 3; HP calculators = 4; Multimedia = 5; Other = 9).
   b. Software (Unspecified = 0; Tutorial = 1; Drill-and-practice = 2; Exploratory environment [e.g., simulations, microworlds, hypermedia, and hypertext] = 3; Tools for other tasks [e.g., word processor for writing, e-mail, or computer-conference for course assignments] = 4; Programming language = 5; Computer-supported Independent Reading Environment=6; Other = 9).
   c. Technology Resources/Support Available (Unspecified = 0; No resources = 1; Minimal resources = 2; Adequate resources = 3; Ample resources = 4; Other = 9).
   d. Role/Focus of Technology (Unspecified = 0; Productivity = 1; Delivery system [e.g., ILS] = 2; Resource [e.g., Internet] = 3; Other = 9).
   e. Quantity of Technology (Unspecified = 0; Few [< 3 per classroom] = 1; Average [4–8 per classroom] = 2; Ample [> 9 per classroom] = 3; Other = 9).
   f. Number of Computer Sessions (Unspecified = 0; List number of sessions [e.g., 12]).
   g. Duration of Computer Sessions (Unspecified = 0; List number of average minutes per sessions [e.g., 40]).
h. Teachers’ Experience with Technology (Unspecified = 0; None = 1; Minimal experience = 2; Average = 3; Experienced = 4; Very experienced = 5).

i. Students’ Experience with Technology (Unspecified = 0; None = 1; Minimal experience = 2; Average = 3; Experienced = 4; Very experienced = 5).

j. Teacher Training in Technology (Unspecified = 0; List hours of training (e.g., 15).

k. Feedback and Assessment Practices (Unspecified = 0; No feedback = 1; Minimal feedback = 2; Elaborate feedback = 3; Other = 9).

l. Learning Responsibility (Unspecified = 0; Student controlled = 1; Teacher directed = 2; System directed = 3; Mixed = 4; Other = 9).

m. Task Difficulty (Unspecified = 0; Difficult = 1; Moderately difficult = 2; Not difficult = 3; Mixed levels of difficulty = 4; Other = 5).

n. Type of Learning Task (Unspecified = 0; Basic skills/factual learning = 1; Problem solving = 2; Inquiry/investigation = 3; Project-based = 4; Mixed types = 5; Other = 9).

o. Type of Technology Program (Unspecified = 0; Basic skills/factual learning = 1; Problem solving = 2; Inquiry = 3; Mixed types = 4; Other = 9).

p. Pattern of Student Computer Use (Unspecified = 0; Teacher use only = 1; Presentation station = 2; One student per computer = 3; Two students per computer = 4; 3–5 students per computer = 4; > 5 students per computer = 6; Mixed pattern = 7; Other = 9).

q. Percentage of Students Using Computers (Unspecified = 0; > 10 percent = 1; 10–25 percent = 2; 26–50 percent = 3; 51–75 percent = 4; 76–90 percent = 5; > 90 percent = 6).

r. Objectives of Computer Use (Unspecified = 0; Remediation of skills not learned = 1; Expressing themselves in writing = 2; Communicating electronically with other people = 3; Finding out about ideas and information = 4; Analyzing information = 5; Presenting information to an audience = 6; Improving computer skills = 7; Learning to work collaboratively = 8; Learning to work independently = 9; Multiple Objectives = 10; Other = 19).

s. AEGIS of Technology (Unspecified=0; commercial venture (e.g., Fast Forward or Acc Reader)=1; experimenter developed=2; externally (feds or foundation) funded=3; 9=other)

6. Instructional/Teaching Characteristics
   a. Joint Productive Activity/Collaboration (e.g., Designs instructional activities requiring student collaboration to accomplish a joint product; monitors and supports students collaboration in positive ways. Unspecified = 0; No evidence = 1; Some evidence = 2; Extensive evidence = 3).
   b. Challenging Activities (e.g., Designs instructional tasks that advance students’ understanding to more complex levels. Assures that students—for each instructional topic—see the whole picture as a basis for understanding the parts. Unspecified = 0; No evidence = 1; Some evidence = 2; Extensive evidence = 3).
   c. Instructional Conversation (e.g, Arranges the classroom to accommodate conversational between the teacher and a small group of students on a regular and frequent basis. Guides conversation to include students’ views, judgments, and
rationales using text evidence and other substantive support. Unspecified = 0; No evidence = 1; Some evidence = 2; Extensive evidence = 3).

d. Setting (Unspecified = 0; Classroom = 1; Networked lab within class = 2; Computer lab in school = 3; Other = 9).

e. Mode of Instruction (Unspecified = 0; Whole-group instruction = 1; Paired = 2; Small-group instruction [3–5 members] = 3; Individualized = 4; Mixed = 5; Other = 9).

f. Role of Teacher (Unspecified = 0; Deliverer of knowledge = 1; Facilitator of groups/student learning = 2; Modeling processes [e.g., problem solving] = 3; Mixed = 4; Observer=5; Other = 9).

g. Teacher Qualifications (Unspecified = 0; Alternatively certified or provisional certificate = 1; Certified in content area = 2; Not certified in content area = 3; Other = 9).

7. Policy

a. Level (Unspecified = 0; School = 1; District = 2; State = 3; Federal = 4; Other = 5).

b. Focus (Unspecified = 0; Reducing achievement gaps = 1; Increased use of technology = 2; Increased specific type of use = 3; Improve Specific Educational Outcomes=4; Other = 9).
## Appendix F

Statistics for the 89 Effect Sizes in the Analysis

<table>
<thead>
<tr>
<th>Study name</th>
<th>Comparison</th>
<th>Hedges's g</th>
<th>Standard error</th>
<th>Variance</th>
<th>Lower limit</th>
<th>Upper limit</th>
<th>Z-Value*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alfassi</td>
<td>Accuracy</td>
<td>-0.237</td>
<td>0.327</td>
<td>0.107</td>
<td>-0.878</td>
<td>0.405</td>
<td>-0.723</td>
</tr>
<tr>
<td>Alfassi</td>
<td>ReadComp</td>
<td>1.674</td>
<td>0.381</td>
<td>0.145</td>
<td>0.928</td>
<td>2.421</td>
<td>4.395</td>
</tr>
<tr>
<td>Alfassi</td>
<td>ReadRate</td>
<td>1.009</td>
<td>0.347</td>
<td>0.120</td>
<td>0.329</td>
<td>1.688</td>
<td>2.907</td>
</tr>
<tr>
<td>Dalton</td>
<td>Read</td>
<td>0.424</td>
<td>0.204</td>
<td>0.042</td>
<td>0.023</td>
<td>0.825</td>
<td>2.075</td>
</tr>
<tr>
<td>Gentry</td>
<td>Digital</td>
<td>0.135</td>
<td>0.279</td>
<td>0.078</td>
<td>-0.411</td>
<td>0.681</td>
<td>0.484</td>
</tr>
<tr>
<td>Gentry</td>
<td>PictAbs Digital</td>
<td>0.342</td>
<td>0.280</td>
<td>0.079</td>
<td>-0.207</td>
<td>0.892</td>
<td>1.221</td>
</tr>
<tr>
<td>Gentry</td>
<td>PictPres Digital</td>
<td>-0.072</td>
<td>0.278</td>
<td>0.078</td>
<td>-0.618</td>
<td>0.473</td>
<td>-0.260</td>
</tr>
<tr>
<td>Fasting</td>
<td>OS400</td>
<td>1.013</td>
<td>0.291</td>
<td>0.084</td>
<td>0.443</td>
<td>1.583</td>
<td>3.485</td>
</tr>
<tr>
<td>Fasting</td>
<td>OS400Follow</td>
<td>0.034</td>
<td>0.273</td>
<td>0.075</td>
<td>-0.502</td>
<td>0.569</td>
<td>0.123</td>
</tr>
<tr>
<td>Fasting</td>
<td>SL60</td>
<td>0.917</td>
<td>0.288</td>
<td>0.083</td>
<td>0.353</td>
<td>1.480</td>
<td>3.188</td>
</tr>
<tr>
<td>Fasting</td>
<td>SL60Follow</td>
<td>0.452</td>
<td>0.277</td>
<td>0.077</td>
<td>-0.090</td>
<td>0.995</td>
<td>1.634</td>
</tr>
<tr>
<td>Fasting</td>
<td>Spelling</td>
<td>1.244</td>
<td>0.299</td>
<td>0.090</td>
<td>0.658</td>
<td>1.830</td>
<td>4.159</td>
</tr>
<tr>
<td>Fasting</td>
<td>SpellingFollow</td>
<td>-0.155</td>
<td>0.274</td>
<td>0.075</td>
<td>-0.691</td>
<td>0.382</td>
<td>-0.565</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>Outcome1</td>
<td>0.653</td>
<td>0.183</td>
<td>0.033</td>
<td>0.295</td>
<td>1.010</td>
<td>3.575</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>Outcome2</td>
<td>0.645</td>
<td>0.182</td>
<td>0.033</td>
<td>0.288</td>
<td>1.003</td>
<td>3.538</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>Outcome3</td>
<td>0.379</td>
<td>0.179</td>
<td>0.032</td>
<td>0.027</td>
<td>0.730</td>
<td>2.111</td>
</tr>
<tr>
<td>Hasselbring</td>
<td>Outcome4</td>
<td>0.405</td>
<td>0.180</td>
<td>0.032</td>
<td>0.053</td>
<td>0.757</td>
<td>2.257</td>
</tr>
<tr>
<td>Henao</td>
<td>DetGood</td>
<td>0.000</td>
<td>0.428</td>
<td>0.183</td>
<td>-0.839</td>
<td>0.839</td>
<td>0.000</td>
</tr>
<tr>
<td>Henao</td>
<td>DetPoor</td>
<td>0.285</td>
<td>0.431</td>
<td>0.185</td>
<td>-0.559</td>
<td>1.129</td>
<td>0.661</td>
</tr>
<tr>
<td>Henao</td>
<td>ImpGood</td>
<td>0.872</td>
<td>0.450</td>
<td>0.202</td>
<td>-0.010</td>
<td>1.754</td>
<td>1.938</td>
</tr>
<tr>
<td>Henao</td>
<td>ImpPoor</td>
<td>1.517</td>
<td>0.491</td>
<td>0.241</td>
<td>0.555</td>
<td>2.479</td>
<td>3.090</td>
</tr>
<tr>
<td>Higgins</td>
<td>Grade</td>
<td>0.514</td>
<td>0.259</td>
<td>0.067</td>
<td>0.006</td>
<td>1.022</td>
<td>1.984</td>
</tr>
<tr>
<td>Higgins</td>
<td>Raw</td>
<td>0.686</td>
<td>0.262</td>
<td>0.069</td>
<td>0.171</td>
<td>1.200</td>
<td>2.613</td>
</tr>
<tr>
<td>Jones</td>
<td>LanExp</td>
<td>0.332</td>
<td>0.193</td>
<td>0.037</td>
<td>-0.046</td>
<td>0.710</td>
<td>1.721</td>
</tr>
<tr>
<td>Jones</td>
<td>LanExp Sessions</td>
<td>0.357</td>
<td>0.193</td>
<td>0.037</td>
<td>-0.021</td>
<td>0.735</td>
<td>1.849</td>
</tr>
<tr>
<td>Jones</td>
<td>LanMech</td>
<td>0.201</td>
<td>0.192</td>
<td>0.037</td>
<td>-0.175</td>
<td>0.578</td>
<td>1.048</td>
</tr>
<tr>
<td>Jones</td>
<td>LanMech Sessions</td>
<td>0.441</td>
<td>0.194</td>
<td>0.037</td>
<td>0.062</td>
<td>0.821</td>
<td>2.280</td>
</tr>
<tr>
<td>Jones</td>
<td>Rcomp</td>
<td>0.413</td>
<td>0.193</td>
<td>0.037</td>
<td>0.034</td>
<td>0.791</td>
<td>2.134</td>
</tr>
<tr>
<td>Jones</td>
<td>Rcomp Sessions</td>
<td>0.140</td>
<td>0.192</td>
<td>0.037</td>
<td>-0.236</td>
<td>0.516</td>
<td>0.729</td>
</tr>
<tr>
<td>Jones</td>
<td>RVocab</td>
<td>0.532</td>
<td>0.194</td>
<td>0.038</td>
<td>0.151</td>
<td>0.912</td>
<td>2.735</td>
</tr>
<tr>
<td>Jones</td>
<td>RVocab Sessions</td>
<td>0.130</td>
<td>0.192</td>
<td>0.037</td>
<td>-0.246</td>
<td>0.507</td>
<td>0.679</td>
</tr>
<tr>
<td>Jones</td>
<td>Spelling</td>
<td>0.265</td>
<td>0.192</td>
<td>0.037</td>
<td>-0.112</td>
<td>0.642</td>
<td>1.376</td>
</tr>
<tr>
<td>Jones</td>
<td>Spelling Sessions</td>
<td>0.530</td>
<td>0.194</td>
<td>0.038</td>
<td>0.149</td>
<td>0.910</td>
<td>2.726</td>
</tr>
<tr>
<td>Kramarski</td>
<td>Metecog</td>
<td>-1.057</td>
<td>0.292</td>
<td>0.085</td>
<td>-1.630</td>
<td>-0.485</td>
<td>-3.618</td>
</tr>
<tr>
<td>Kramarski</td>
<td>Motiv</td>
<td>0.704</td>
<td>0.282</td>
<td>0.079</td>
<td>0.152</td>
<td>1.256</td>
<td>2.499</td>
</tr>
<tr>
<td>Kramarski</td>
<td>Rcomp</td>
<td>-0.259</td>
<td>0.274</td>
<td>0.075</td>
<td>-0.797</td>
<td>0.278</td>
<td>-0.945</td>
</tr>
<tr>
<td>Leu</td>
<td>Control High</td>
<td>0.836</td>
<td>0.303</td>
<td>0.092</td>
<td>0.242</td>
<td>1.429</td>
<td>2.759</td>
</tr>
<tr>
<td>Leu</td>
<td>Control Lo</td>
<td>0.943</td>
<td>0.313</td>
<td>0.098</td>
<td>0.330</td>
<td>1.555</td>
<td>3.014</td>
</tr>
<tr>
<td>Leu</td>
<td>Control Med</td>
<td>0.888</td>
<td>0.314</td>
<td>0.099</td>
<td>0.272</td>
<td>1.504</td>
<td>2.824</td>
</tr>
<tr>
<td>Leu</td>
<td>DrpCtrl High</td>
<td>0.223</td>
<td>0.291</td>
<td>0.085</td>
<td>-0.348</td>
<td>0.793</td>
<td>0.765</td>
</tr>
<tr>
<td>Leu</td>
<td>DrpCtrl Lo</td>
<td>0.016</td>
<td>0.296</td>
<td>0.088</td>
<td>-0.564</td>
<td>0.596</td>
<td>0.054</td>
</tr>
<tr>
<td>Leu</td>
<td>DrpCtrl Med</td>
<td>0.116</td>
<td>0.300</td>
<td>0.090</td>
<td>-0.471</td>
<td>0.704</td>
<td>0.388</td>
</tr>
<tr>
<td>Ligas</td>
<td>6:95-96</td>
<td>-0.143</td>
<td>0.060</td>
<td>0.004</td>
<td>-0.261</td>
<td>-0.024</td>
<td>-2.363</td>
</tr>
<tr>
<td>Ligas</td>
<td>6:96-97</td>
<td>-0.084</td>
<td>0.060</td>
<td>0.004</td>
<td>-0.202</td>
<td>0.035</td>
<td>-1.388</td>
</tr>
<tr>
<td>Ligas</td>
<td>6:97-98</td>
<td>-0.174</td>
<td>0.060</td>
<td>0.004</td>
<td>-0.293</td>
<td>-0.056</td>
<td>-2.884</td>
</tr>
<tr>
<td>Ligas</td>
<td>6:98-99</td>
<td>-0.153</td>
<td>0.060</td>
<td>0.004</td>
<td>-0.271</td>
<td>-0.034</td>
<td>-2.531</td>
</tr>
<tr>
<td>Study name</td>
<td>Comparison</td>
<td>Hedges's g</td>
<td>Standard error</td>
<td>Variance</td>
<td>Lower limit</td>
<td>Upper limit</td>
<td>Z-value*</td>
</tr>
<tr>
<td>------------</td>
<td>---------------------</td>
<td>------------</td>
<td>----------------</td>
<td>----------</td>
<td>-------------</td>
<td>-------------</td>
<td>----------</td>
</tr>
<tr>
<td>Ligas</td>
<td>Hrs12+5-</td>
<td>0.698</td>
<td>0.168</td>
<td>0.028</td>
<td>0.368</td>
<td>1.028</td>
<td>4.147</td>
</tr>
<tr>
<td>Liu</td>
<td>LS Science</td>
<td>1.676</td>
<td>0.416</td>
<td>0.173</td>
<td>0.861</td>
<td>2.492</td>
<td>4.029</td>
</tr>
<tr>
<td>Liu</td>
<td>RegEdScience</td>
<td>3.047</td>
<td>0.194</td>
<td>0.038</td>
<td>2.666</td>
<td>3.428</td>
<td>15.675</td>
</tr>
<tr>
<td>Liu</td>
<td>Tag Science</td>
<td>3.314</td>
<td>0.425</td>
<td>0.180</td>
<td>2.482</td>
<td>4.146</td>
<td>7.806</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>CompAll</td>
<td>1.011</td>
<td>0.259</td>
<td>0.067</td>
<td>0.504</td>
<td>1.518</td>
<td>3.908</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>CompSE</td>
<td>0.754</td>
<td>0.252</td>
<td>0.064</td>
<td>0.261</td>
<td>1.248</td>
<td>2.994</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>CompText</td>
<td>-0.108</td>
<td>0.243</td>
<td>0.059</td>
<td>-0.586</td>
<td>0.369</td>
<td>-0.445</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>LEALL</td>
<td>-0.247</td>
<td>0.244</td>
<td>0.060</td>
<td>-0.725</td>
<td>0.232</td>
<td>-1.010</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>LESE</td>
<td>-0.231</td>
<td>0.244</td>
<td>0.060</td>
<td>-0.709</td>
<td>0.248</td>
<td>-0.944</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>LETE</td>
<td>-0.368</td>
<td>0.245</td>
<td>0.060</td>
<td>-0.849</td>
<td>0.113</td>
<td>-1.498</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>PRALL</td>
<td>-0.351</td>
<td>0.245</td>
<td>0.060</td>
<td>-0.831</td>
<td>0.130</td>
<td>-1.430</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>PRSE</td>
<td>-0.189</td>
<td>0.244</td>
<td>0.059</td>
<td>-0.667</td>
<td>0.289</td>
<td>-0.774</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>PRTE</td>
<td>-0.349</td>
<td>0.245</td>
<td>0.060</td>
<td>-0.829</td>
<td>0.132</td>
<td>-1.422</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>Rall</td>
<td>1.831</td>
<td>0.291</td>
<td>0.085</td>
<td>1.261</td>
<td>2.401</td>
<td>6.297</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>Rase</td>
<td>0.745</td>
<td>0.252</td>
<td>0.063</td>
<td>0.251</td>
<td>1.238</td>
<td>2.959</td>
</tr>
<tr>
<td>Reinking 88</td>
<td>Rate</td>
<td>0.067</td>
<td>0.243</td>
<td>0.059</td>
<td>-0.410</td>
<td>0.544</td>
<td>0.274</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Compall</td>
<td>0.631</td>
<td>0.364</td>
<td>0.133</td>
<td>-0.084</td>
<td>1.345</td>
<td>1.731</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Comp glo</td>
<td>0.354</td>
<td>0.358</td>
<td>0.128</td>
<td>-0.348</td>
<td>1.056</td>
<td>0.989</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Comp sel</td>
<td>0.362</td>
<td>0.358</td>
<td>0.128</td>
<td>-0.340</td>
<td>1.064</td>
<td>1.010</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Defs</td>
<td>0.833</td>
<td>0.371</td>
<td>0.138</td>
<td>0.105</td>
<td>1.561</td>
<td>2.244</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>VALL</td>
<td>1.452</td>
<td>0.402</td>
<td>0.161</td>
<td>0.665</td>
<td>2.240</td>
<td>3.615</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>VGlo</td>
<td>0.044</td>
<td>0.355</td>
<td>0.126</td>
<td>-0.652</td>
<td>0.741</td>
<td>0.124</td>
</tr>
<tr>
<td>Reinking 90</td>
<td>Vsel</td>
<td>1.163</td>
<td>0.386</td>
<td>0.149</td>
<td>0.407</td>
<td>1.919</td>
<td>3.016</td>
</tr>
<tr>
<td>Rouse</td>
<td>CompReadEdge</td>
<td>0.057</td>
<td>0.093</td>
<td>0.009</td>
<td>-0.126</td>
<td>0.239</td>
<td>0.609</td>
</tr>
<tr>
<td>Rouse</td>
<td>Overall CELF</td>
<td>0.062</td>
<td>0.214</td>
<td>0.046</td>
<td>-0.357</td>
<td>0.481</td>
<td>0.289</td>
</tr>
<tr>
<td>Rouse</td>
<td>SFA Assess</td>
<td>0.059</td>
<td>0.104</td>
<td>0.011</td>
<td>-0.144</td>
<td>0.262</td>
<td>0.566</td>
</tr>
<tr>
<td>Rouse</td>
<td>State Read Test</td>
<td>0.063</td>
<td>0.094</td>
<td>0.009</td>
<td>-0.121</td>
<td>0.247</td>
<td>0.675</td>
</tr>
<tr>
<td>Salomon</td>
<td>CntExpComp</td>
<td>1.395</td>
<td>0.311</td>
<td>0.097</td>
<td>0.785</td>
<td>2.005</td>
<td>4.480</td>
</tr>
<tr>
<td>Salomon</td>
<td>CtrlExpComp</td>
<td>1.730</td>
<td>0.331</td>
<td>0.110</td>
<td>1.081</td>
<td>2.379</td>
<td>5.226</td>
</tr>
<tr>
<td>Solan</td>
<td>TechnoRead</td>
<td>0.664</td>
<td>0.365</td>
<td>0.134</td>
<td>-0.053</td>
<td>1.380</td>
<td>1.816</td>
</tr>
<tr>
<td>Underwood</td>
<td>ILS</td>
<td>-0.027</td>
<td>0.174</td>
<td>0.030</td>
<td>-0.367</td>
<td>0.314</td>
<td>-0.153</td>
</tr>
<tr>
<td>Volland</td>
<td>Edinburgh</td>
<td>0.657</td>
<td>0.352</td>
<td>0.124</td>
<td>-0.033</td>
<td>1.347</td>
<td>1.867</td>
</tr>
<tr>
<td>Volland</td>
<td>Edinburgh B</td>
<td>-0.472</td>
<td>0.289</td>
<td>0.084</td>
<td>-1.038</td>
<td>0.094</td>
<td>-1.633</td>
</tr>
<tr>
<td>Volland</td>
<td>Neale Acc</td>
<td>0.326</td>
<td>0.405</td>
<td>0.164</td>
<td>-0.468</td>
<td>1.120</td>
<td>0.805</td>
</tr>
<tr>
<td>Volland</td>
<td>Neale Acc B</td>
<td>0.150</td>
<td>0.403</td>
<td>0.162</td>
<td>-0.639</td>
<td>0.940</td>
<td>0.373</td>
</tr>
<tr>
<td>Volland</td>
<td>Neale Comp</td>
<td>1.403</td>
<td>0.452</td>
<td>0.205</td>
<td>0.517</td>
<td>2.290</td>
<td>3.102</td>
</tr>
<tr>
<td>Volland</td>
<td>Neale Comp B</td>
<td>0.178</td>
<td>0.403</td>
<td>0.163</td>
<td>-0.612</td>
<td>0.968</td>
<td>0.441</td>
</tr>
<tr>
<td>Xin</td>
<td>Cloze Follow</td>
<td>0.024</td>
<td>0.227</td>
<td>0.052</td>
<td>-0.421</td>
<td>0.470</td>
<td>0.108</td>
</tr>
<tr>
<td>Xin</td>
<td>Cloze Post</td>
<td>0.368</td>
<td>0.229</td>
<td>0.052</td>
<td>-0.081</td>
<td>0.817</td>
<td>1.606</td>
</tr>
<tr>
<td>Xin</td>
<td>Comp Follow</td>
<td>0.112</td>
<td>0.227</td>
<td>0.052</td>
<td>-0.334</td>
<td>0.558</td>
<td>0.493</td>
</tr>
<tr>
<td>Xin</td>
<td>Comp Post</td>
<td>0.245</td>
<td>0.228</td>
<td>0.052</td>
<td>-0.202</td>
<td>0.692</td>
<td>1.075</td>
</tr>
<tr>
<td>Xin</td>
<td>Word Follow</td>
<td>0.359</td>
<td>0.229</td>
<td>0.052</td>
<td>-0.090</td>
<td>0.808</td>
<td>1.566</td>
</tr>
<tr>
<td>Xin</td>
<td>Word Post</td>
<td>0.475</td>
<td>0.230</td>
<td>0.053</td>
<td>0.024</td>
<td>0.927</td>
<td>2.062</td>
</tr>
<tr>
<td><strong>Random Effects Model</strong></td>
<td><strong>Weighted Mean</strong></td>
<td>0.489</td>
<td>0.112</td>
<td>0.013</td>
<td>0.269</td>
<td>0.709</td>
<td>4.360</td>
</tr>
</tbody>
</table>

* for \( Z=1.96, p<.05 \); for \( Z=2.58, p<.01 \)
Appendix G. Bibliographies


186. Tsai, M.-J. (2002). Do male students often perform better than female students when learning computers?: A study of Taiwanese eight graders’ computer education through strategic and cooperative learning. *Journal of Educational and Computing Research, 26*(1), 67–85.


