Mathematics Achievement and Orientation:
A Systematic Review and Meta-Analysis of Education Technology

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1. Introduction

The use of digital technology in the teaching and learning of mathematics, a practice that has been discussed and promoted for decades as a fundamental principle of mathematics education (National Council of Teachers of Mathematics (NCTM), 1989, 2000, 2014), has resulted in a wide array of studies. The most common student outcome studied in relation to technology use is achievement, followed by orientation (i.e., the affective domain; Ronau et al., 2014). Existing reviews have examined both outcomes in relation to particular technologies (e.g., calculators in Ellington, 2003; graphing calculators in Ellington, 2006; computer technology in Li & Ma, 2010). These meta-analyses did not account for clustering effects (e.g., students nested in teachers) and therefore likely over-estimated the true effects found in their primary studies (Hedges, 2007). Furthermore, while the meta-analyses examined both achievement and orientation, they examined the outcomes separately with different samples of studies. Their analyses were therefore unable to account for the relationship between the two outcomes (*dependent variable correlation*), which also potentially over-estimates effect sizes (Kalaian & Kasim, 2008). Finally, the potential for effect sizes to be inflated by publication bias, the tendency for statistically significant results to be published at higher rates than non-significant results (Rothstein, Sutton, & Borenstein, 2006), has not been consistently analyzed in mathematics education technology meta-analyses. Some meta-analyses (e.g., Ellington, 2000) do include grey literature (e.g., dissertations, theses, reports), which does help alleviate effect size inflation (Conn, Valentine, Cooper, & Rantz, 2003). Even with grey literature inclusion, the absence of a robust publication bias analysis opens the possibility that their reported effect sizes are higher than the true effects (Stanley, 2017).

A comprehensive examination of achievement and orientation across technologies can provide a clearer view of how technology has been used to improve the teaching of mathematics. Accounting for clustering, dependent variable relationships, and publication bias provides a more robust estimate of true effect sizes on student achievement and orientation.

1.1 Focus of the Study

The present study provides a meta-analysis of comprehensive technology use in mathematics education and the effects on student achievement and orientation. The analysis accounts for both clustering effects and multicollinearity between achievement and orientation, thereby yielding a more precise estimate of true effects.

Seven different types of technology and six different uses of technology were identified. The combination of different technology types and uses in the analysis may limit some of the explanatory power on individual technologies, so the analyses of specific individual technologies and uses are also included. In addition to investigating the gross overall achievement and orientation effects, we analyzed the moderating effects of individual technologies, technology uses, student characteristics, study characteristics, and outcomes.

The mathematics education field has long recognized that simply incorporating technology into classroom instruction will have no effect on learning by itself (Cohen & Hollebrands, 2011; Roschelle et al., 2000; Roschelle et al., 2010; Sickel, 2019). There is a general understanding that technology serves as a vehicle for implementing pedagogical changes (Clark, 1983; NCTM, 2014; Roschelle et al., 2010). Technology is generally considered effective to the degree it is used in a way that improves student conceptual understanding of mathematics and encourages mathematical reasoning and communication (NCTM, 2014). An analysis of conceptual emphasis in technology interventions was therefore included as an additional dimension for understanding the way technology uses were coupled with pedagogy in the mathematics classroom. Because confounding influences are an ever-present reality in technology research (Clark, 1983, 1994), we remained cognizant of Sickel's (2019) caution against overstating and overgeneralizing results.

1.2 Research Questions

The study investigated two questions.

1. What are the effects on achievement and orientation, accounting for dependent variable correlation, clustering and publication bias?
2. To what extent was conceptual understanding an emphasis of mathematics education technology research?

2. Literature Review and Conceptual Framework

The present study identified five factors that contribute to the nature of a mathematics education technology intervention study: technology type, technology use, conceptual emphasis, study characteristics, and student characteristics. The model for this study's conceptual framework shows these five factors influencing the intervention, which in turn influences student achievement and orientation outcomes (Figure 1).

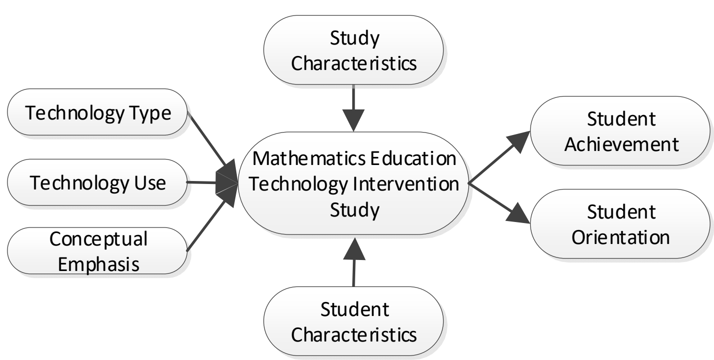

Figure 1. Model of Study Conceptual Framework

2.1 Technology Type

The term *mathematics education technology* refers in the present study to digital technologies, which were organized into five categories: calculators, probeware, software, hardware, and Internet. Calculators consisted of four-function, scientific, graphing calculators, calculator programming and applications, computer algebra systems (CAS), dynamic geometry, simulation, networked-handheld devices, and statistics. Probeware consisted of data collection devices such as Calculator Based Laboratory (CBLTM), Computer Based Ranger (CBRTM), motion detectors, and other specialized sensors (e.g., temperature, pressure, velocity). Software consisted of dynamic geometry, graphing, algebra, statistics, statistics instruction, spreadsheet, presentation, applets, games/puzzles, testing, tutorial, student response systems, and interactive whiteboard. Hardware consisted of laptops, classroom computers, and computer labs. Internet technologies included online manipulatives and applets, distance learning, online games/puzzles, online testing, online tutorial, websites, WebQuests, Wiki spaces, social media (e.g., Facebook, Twitter), video conferencing, document or video sharing, and blogs.

The value of technology lay less in the software or hardware and more on how it is integrated with pedagogy and curriculum (Dick & Hollebrands, 2011; Roschelle et al., 2010). Large scale studies of "technology effects" typically find null effects, for example Campuzano et al.'s (2009) examination of PLATO Achieve Now 6th grade mathematics, which engages students in independent practice and reinforcement of mathematics skills and Larson's Pre-Algebra 6th grade mathematics, which provides an online text to supplement the hard copy textbook with instruction, practice, and assessment. Although the type of technology does not directly affect student outcomes by itself, the characteristics of the technology provide an avenue for effectively enhancing pedagogy (NCTM, 2014). Given the crossover of characteristics between different technology types (e.g., online dynamic geometry software, graphing calculator dynamic geometry applications, and desktop dynamic geometry programs), a breakdown by type of technology is unlikely to render strong inferences but is included in Online Supplement B for reference purposes. Technology use and conceptual emphasis offer two perspectives on how technology is integrated with pedagogy.

2.2 Technology Use

Technology use describes how technology is integrated into pedagogy. Six broad categories of technology use were identified in the literature: instruction enhancement, computation, support for active learning, tutorial, assessment, and technology-rich environments. Instruction enhancement consisted of a wide array of activities. Most common was using technology as a supplement to regular classroom activities (e.g., Bai, Pan, Hirumi, & Kebritchi, 2012; Kim, 2007; Santiago-Collazo, 1995). Almost as common was using technology to perform or check computations (e.g., Harter, 2006; Isiksal & Askar, 2005; Ke, 2006). Active learning uses of technology included geometry explorations (e.g., Hodanbosi, 2001), graphing calculator investigations (e.g., Fox, 1998), inquiry learning (e.g., Pilli & Aksu, 2013; Yang, 2014), algebra projects (e.g., Buck, 2009; Ogbuehi & Fraser, 2007), and data investigations (e.g., Spinelli, 2001). Some studies engaged students with tutorial features of graphing calculators (e.g., Mirick, 2002), computer programs (e.g., May, 2005; Voloshin, 2009; Zunker, 2008), and distance learning software (e.g., Spence, 2004). Using technology to support mathematics assessment consisted of student calculator use during a test (e.g., Bouck & Bouck, 2008; Ellerman, 1998) and online testing systems (e.g., Hurn, 2006). Some studies did not clearly explain how teachers or students were using technology. Some studies examined technology-rich mathematics classrooms (e.g., Bolin, 1992). Others provided students with time to work freely in a computer lab (e.g., Wodarz, 1994).

2.3 Conceptual Emphasis

Conceptual emphasis is a second consideration of how technology is used in mathematics education, measuring the emphasis of the assessment items used in the achievement measure(s). The ability of technology to support conceptual understanding is particularly important (Kaput, Hegedus, & Lesh, 2007; Roshchelle et al., 2010). Erlwanger (2004) found that if a student already has conceptual understanding, the use of technology for basic fact recall and procedures is unlikely to impede student learning. But if conceptual understanding is not already present, using technology for basic fact recall and procedures will not help develop it; in fact, it may help develop and strengthen misconceptions.

2.4 Student Characteristics

Student characteristics (e.g., gender, ability) influence the degree to which technology can be used to effectively improve mathematics teaching and learning (Li & Ma, 2010). Student characteristics are typically included as moderators in a meta-analysis. Ma (1999) found no significant difference in the relationship between anxiety and achievement by grade level, comparing grades 4-6 to grades 10-12 and grades 7-9 to grades 10-12. In addition, the effect of sex was not significant. Student ability level was not examined. Hembree and Dessart (1986) and Ellington (2003) found that grade level moderated calculator effects on student achievement. Ellington (2003) found that ability levels also moderated calculator effects on student achievement. Li and Ma (2010) found significant effects from special education status and grade level.

2.5 Study Characteristics

Study characteristics (e.g., design, procedures, analytic methods) influence the validity of measured effects in a meta-analysis. Study characteristics are typically included as moderators in a meta-analysis. For example, Ellington (2003) found differences in effects based on publication status and treatment length. Li and Ma (2010) found significant effects from the method of teaching (constructivist versus traditional approach) and year of publication (before and after 1999).

Planning for effective pedagogy involving technology follows a sequence: learning objective → appropriate task → appropriate tool(s) (Cohen & Hollebrands, 2011). Research studies often do not follow such a sequence. Researchers typically have a type of technology and may even have a particular lesson, sequence, or curriculum as part of the intervention (e.g., Bai et al., 2012; Ersoy & Akbulut, 2014; Roschelle et al., 2010; Smith, 1991). Teachers are then asked to adopt the intervention package, or the intervention happens outside of mathematics classroom. These typical research features raise validity concerns. For example, Roschelle et al. (2010) noted that their intervention was a replacement unit and that they were not concerned in Year 1 with high treatment fidelity and only attended to it minimally in Year 2. In some cases (e.g., Bai et al., 2012; Pilli & Aksu, 2013; Ross, Bruce, & Sibbald, 2011), particular technology is studied, and indication is infrequently given that researchers considered a range of tools when planning curriculum materials to accompany the technology.

The independent variable in mathematics education technology research is often intermingled with pedagogy, making interpretation of effects difficult at best. Control conditions are typically some form of "business as usual" (e.g., Ellerman, 1998; Fletcher, Hawley, & Piele, 1990). Some studies do not specify technology-supported pedagogical enhancements at all: students received the same content and problems with and without technology (e.g., Feliciano, 1996).

Most studies that compare two types of technology use them differently in the same lesson (e.g., Abramowitz, 1999; Fox, 1998; Hylton-Lindsay, 1997; Yang, 2014), so effects cannot be attributed to the technology use alone. Brown (2007) is an exception, comparing the use of virtual and concrete manipulatives with similar pedagogy for the same lessons. Chen (2005) is another exception, comparing computer algebra instruction with personalized questions to computer algebra instruction without personalized questions. Effects for Chen (2005) therefore represent the effects of personalized questions rather than computer algebra instruction.

2.6 Student Achievement

Student achievement is a measure of a type of knowledge, and test scores are a measure of that achievement (e.g., departmental final exam in Brewer, 2009; standardized tests in Duffy & Thompson, 1980 and Plourde, 2008). Achievement and learning are inter-related but distinct. While student learning is the growth in knowledge, achievement is the status of a type of knowledge at a particular point in time (Linn et al., 2013).

2.7 Student Orientation

Student *Orientation* is a term coined by Schoenfeld (2011) to refer to the affective domain as a whole and includes attitudes, beliefs, dispositions, and preferences. Orientations toward mathematics and/or technology have been studied extensively, including in relation to technology in mathematics education. For example, Hembree and Dessart (1986) and Ellington (2003) examined attitudes and perceptions of mathematics in relation to calculator use. Hoffman (2010) and Ma (1999) examined mathematics anxiety. Hoffman (2010) also examined students' sense of mathematics efficacy. Other orientation constructs that have been studied extensively include beliefs (Phillip et al., 2007; Schoenfeld, 1982, 1985, 1989), value of mathematics (Phillip et al., 2007; Tapia & Marsh, 2004), goals (Phillip et al., 2007), confidence (Fennema &

Sherman, 1976; Tapia & Marsh, 2004), enjoyment (Tapia & Marsh, 2004), and motivation (Tapia & Marsh, 2004). Fennema and Sherman (1976) examined attributions/attitudes toward success, perceptions of parental interest, encouragement, and perceptions of teacher attitudes.

2.8 The Importance of Studying Achievement and Orientation Together

There are several reasons to examine achievement and orientation outcomes together when studying mathematics education technology research. First, effective technology integration into pedagogy may result in improved achievement (e.g., Roschelle et al., 2010), student engagement and/or self-directed learning (Baki & Guven, 2009; Chen, 2008; Goodwin & Miller, 2013; Roschelle et al., 2000), mathematics confidence and motivation (Galbraith & Haines, 1998), or technology confidence and motivation. Orientation measures can provide insight into the way(s) students interacted with the technology. Student lack of familiarity/comfort with the technology can impede engagement (Galbraith & Haines, 1998).

Second, a relationship between achievement and orientation has long been recognized (Aiken, 1970, 1976; Ma, 1999; Neale, 1969). Deep learning is not strictly cognitive but evokes an emotional response, requiring an affective commitment from both students and teachers. Enthusiasm of both students and teachers is central to the learning process (Shulman & Wilson, 2004).

Third, orientation can have a direct influence on student learning. For example, the way mathematics is taught can send implicit messages about what is valued and how various ideas are or are not related (Schoenfeld, 1988). Students' learning experiences shape their beliefs, dispositions, value, and efficacy toward mathematics (Schoenfeld, 2011). Those orientations directly influence the way students approach mathematics in and out of school settings (Schoenfeld, 1982, 1988, 1989, 2011).

2.9 Connections to the present study

This conceptual framework and its underlying research guided the research questions, methods, and analytic techniques of the present study. The use of multilevel multivariate meta-analysis techniques provided a robust analytic tool for measuring effect sizes for achievement and orientation after accounting for their relationship. The inclusion of conceptual emphasis broadened the analysis of how technology was used in research to improve mathematics pedagogy.

3. Method

The present study was part of a larger mathematics education technology project that began with the development of a coding system to identify study characteristics (described in more detail in Ronau et al., 2015). The larger study examined the quality of 1,476 mathematics education technology papers; the present study is a unique examination of only papers that met all the inclusion criteria.

3.1 Design

This systematic review and meta-analysis followed an embedded mixed methods design (Creswell & Plano Clark, 2007). In this embedded mixed methods design, quantitative and qualitative data on student mathematics achievement and orientation were collected simultaneously, and the qualitative data provided a supportive, secondary role by providing contextual and informational nuance for the analyses. Both research questions were primarily investigated using quantitative methods (e.g., effect size computation, multivariate multilevel meta-analysis). The qualitative analyses provided important insight into the types of orientation that were present in the sample studies. The qualitative analyses were also foundational to the analysis of conceptual emphasis in the sample studies.

3.2 Data Collection and Inclusion Criteria

Studies were identified through a systematic process based on the techniques outlined by Cooper, Hedges, and Valentine (2009) and Lipsey and Wilson (2001); for example, defining constructs prior to coding, defining keywords prior to conducting the literature search, defining a coding process, training coders, and cross-checking results. Inclusion in the sample was based on six criteria:

1. The study examined a technology-based intervention.
2. The study examined the learning of a mathematics concept or procedure (e.g., mathematics, algebra, geometry, visualization, representation).
3. The study design included a treatment and control group.
4. The study measured both student achievement and orientation.
5. The achievement and orientation measures were quantitative with sufficient information for computing an effect size.
6. The study needed to be attainable in the English language.

Carter et al. (2019), Conn et al. (2003), and Song, Hooper, and Loke (2013) noted that the best defense against publication bias (the tendency to publish primarily positive, statistically significant effects) is a comprehensive search of the literature that includes grey literature, research that is accepted based on its scientific merits rather than significance of findings (Rothstein & Hopewell, 2009). Grey literature was therefore included such as dissertations, master's theses, and technical reports.

The following database platforms were searched: EBSCOWeb (ERIC, Academic Search Premier, PsychInfo, Primary Search Plus, Middle Search Plus, Education Administration Abstracts), JSTOR (limited to the following disciplines: education, mathematics, psychology, and statistics), OVID, ProQuest (Research Library, Dissertations & Theses, Career & Technical Education), and H.W. Wilson Web (Education Full Text). References from the papers identified through this search were examined to identify potentially relevant papers that were missed in these electronic searches.

Search terms were organized into three categories: technology, mathematics, and education. For technology, we used search terms such as technology, calculate* (* is a wild card), software, Sketchpad, Geogebra, Wingeom, Cabri, TI, digital, dynamic, virtual, applet, web, Excel, spreadsheet, PowerPoint, tablet, computer, microcomputer, podcast, distance learning, CBL, CBR, probe, handheld, hand-held, hand held, visualization, 3d, 3-d, or robot. For education, we used search terms such as education, teach, learn, class, school, student, college, or train*. For mathematics, we used search terms such as math, geometry, algebra, fraction, rational, number, integer, variable, function, equation, expression, calc, probability, statistics, discrete, matrix, coordinate, or transform. Variants of each term were tried (e.g., plural vs. singular, prefixes vs. whole words) to prevent papers from being missed. Bibliographies from identified papers were examined to locate any potentially relevant papers that were not produced in the electronic searches. We also consulted with colleagues to identify any papers that may not have been indexed by a database but might be relevant (e.g., unpublished reports).

The initial search identified 1,476 potentially relevant studies from 1968 to 2014. Studies were not excluded based on the year of publication. The inclusion of older studies was both acceptable and desirable for the following reasons. First, the focus on conceptual understanding versus procedures began far earlier than 1968 (e.g., Brownell, 1935). Second, traditional pedagogy focusing on rote procedures has remained the dominant focus in mathematics classrooms (Hiebert & Grouws, 2007; Stigler & Hiebert, 1997; Welch, 1978). Third, technology has changed rapidly over time, so understanding how technology broadly influences student achievement and orientation requires understanding its uses with both older and newer technologies. Fourth, Ronau et al. (2015) found that research quality remained stable across time. These trends led to the conclusion that an arbitrary date limitation would reduce the sample's representativeness. Figure 2 illustrates the flow of information as studies were identified and examined for inclusion eligibility.

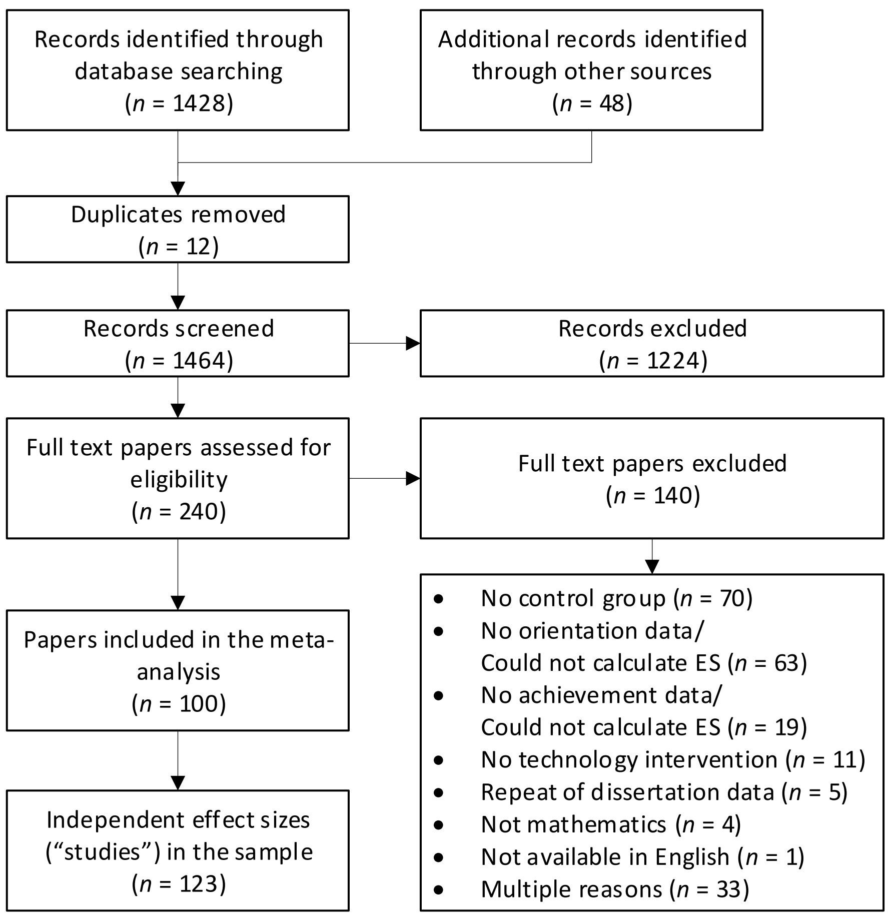

Figure 2. Flowchart of study selection (Adapted from Moher, Liberati, Tetzlaff, Altman, & PRISMA Group, 2009). Note: 33 full text articles were excluded for multiple reasons. ES = Effect Size.

3.3 Inter-Rater Reliability

A counterbalanced design was used to screen papers to improve inter-rater reliability in the screening process. Each researcher was paired with each of the others (i.e., six researchers, each paired with the other five for a total of 15 coder teams). A random number was computed for each paper in Microsoft Excel, papers were then listed in a random order, and pairs of coders were assigned to papers. Within each pair, each member was designated as primary for a set of papers and as secondary for their partners' papers. Once primary coders completed a paper, the secondary coder was notified, who then reviewed, confirmed, or questioned each decision. As a result, 1,224 papers were excluded from the study, leaving 240 for coders to further examine the full text for eligibility.

At least two coders examined the full text to make decisions about whether a paper should be included, resulting in an additional 140 papers (of the 240) being excluded from the sample. After all papers were coded, one coder analyzed the exclusion rationale using open coding (Corbin & Strauss, 2008) and independently wrote memos (Grbich, 2007), which included patterns evident in the reasons for exclusion (listed in Figure 1). A second coder validated the coding and patterns. The full team then discussed the findings to ensure all patterns were agreed upon.

The computation of effect sizes and coding of potential moderating variables were carried out by two coders independently. This double-coding process helped maximize inter-rater reliability and construct validity. Intra-class correlations (ICC) were computed for achievement and orientation effect sizes for each pair of coders. For the achievement effect size, the ICC ranged from .942 to .997 across coder pairs. For the orientation effect sizes, the ICC ranged from .995 to .997. The cross-validation process resulted in 190 of the 240 papers having full initial agreement prior to discussions (79%). The inter-rater reliability was therefore considered to be high. The coder pairs discussed all discrepancies and arrived at a consensus for the final data, which helped ensure that decisions remained true to the desired constructs (i.e., construct validity, for example differentiating between measures of student cognition versus orientation).

3.4 Quality Issues in Excluded Studies

Study quality contributed to exclusion from the sample. The most common reason for exclusion was the lack of a control group for one or both student outcomes (N = 70, 50% of excluded papers). The lack of a control group was considered a quality issue. Although single group studies and analyses are reasonable for some contexts and research questions, they are limited in their ability to provide evidence that an intervention has causal positive effects on the outcomes and that those effects are generalizable (Shadish, Cook, & Campbell, 2002). More puzzling, however, were the large percentage of studies that contained both a treatment and control group, and both achievement and orientation measures, but did not use both measures on both groups (N = 31, 22% of excluded papers). Such results may reveal a limitation in the study's conceptual framework for connecting the multiple outcomes and its potential to contribute to the knowledge base.

The second most common reason for exclusion was the lack of orientation data or enough information to compute an orientation effect size (N = 63, 45% of excluded papers). If a study did not examine student orientation as an outcome, then the lack of orientation data would not be a quality issue. These 63 studies, however, did include orientation outcomes. The lack of data or information about orientation seemed to indicate that a stronger design was planned for achievement than for orientation outcomes, which suggests a potential quality issue.

For 19 of the studies, achievement data were not available, or the study provided insufficient information to compute an effect size. Eight studies provided qualitative information only about achievement, or the focus of the study was teachers instead of students. These issues were not considered to be about quality, simply a different focus of the studies. The other 11 studies, however, were excluded because of quality issues. Three studies provided only aggregated treatment-control results. Seven studies provided means without standard deviations (or alternative statistics that could have been used to compute the effect size such as a focused F test).

Papers that did not include a technology (N = 11, 7.9% of excluded papers) or mathematics intervention (N = 4, 2.9% of excluded papers) had remained in the larger sample because they still had a technology or mathematics component, but the intervention itself was not technology or mathematics based. This issue was not considered to be a quality issue but an anomaly of electronic database searches capturing search terms used in more than one way (e.g., visualization).

Thirty-three papers (23.6% of the excluded papers) were excluded for more than one reason. The most frequent pattern of multiple exclusion categories was no control group data and orientation data were qualitative only/or missing key reporting measures (e.g., means with no standard deviations). After excluding the 140 papers, the sample consisted of 100 papers with 123 independent effect sizes, hereafter referred to as studies.

3.5 Independence of Effect Sizes

In most studies that met the inclusion criteria, more than one achievement and/or orientation effect size was obtainable for a sample of students due to multiple subscales on a single instrument or multiple instruments. For example, Abramowitz (1999) reported 11 achievement measures for the same group of treatment and control students (item format, content of the question, type of understanding). Some studies measured the same construct multiple ways (e.g., two versions of an assessment) or at multiple times (e.g., at posttest and at follow-up). Such measures were aggregated into a single weighted average effect size as recommended by Lipsey and Wilson (2001), thereby ensuring that the data were independent at the sample level.

In some cases, the samples of various subscales and assessments overlapped but lacked or gained a few students so that the sample sizes of each dependent effect size varied slightly. In these cases, the final sample size used was the minimum of the sample sizes to avoid over-weighting the study. The standard errors for the average effect size was computed using the final sample sizes.

In other studies, different samples were studied with no overlap (e.g., two years, two different samples for both treatment and control groups). For these studies, each effect size was independent at the sample level, so both were included in the meta-analysis. For example, Duffy and Thompson (1980) compared three separate treatment and control groups at different grade levels. These non-overlapping studies within a single paper resulted in three independent effect sizes for achievement and orientation.

Five journal articles presented findings from dissertations that were also included in the sample. In every case, these dissertations included measures (both statistically significant and non-significant) that were not included in the journal articles (selective non-reporting bias, as in Boutron et al., 2019). The decision was therefore made to retain the dissertations and exclude the five journal articles (3.6% of the excluded papers) to preserve independence at the sample level.

3.6 Analytic Methods

The analytic process began with the computation of effect sizes. Effect sizes were adjusted in the analyses to address clustering effects and dependent variable correlation. Multiple publication bias analyses were conducted to evaluate the potential for effect size inflation and to estimate a true effect after adjusting for potential bias.

3.6.1 *Effect Size Computation*

The standardized mean difference effect size (Borenstein, 2009; Lipsey & Wilson, 2001) was used to measure the effects of technology interventions between treatment and control groups on student achievement and orientation. The standardized mean difference divides the mean difference by the pooled standard deviation and can be interpreted as a number of standard deviations (Lipsey & Wilson, 2001). Although Hedge's *g* is often used to adjust the standardized mean difference for small sample sizes, the correlation between the standardized mean difference and Hedge's g was greater than .999 for both achievement and orientation, rendering the adjustment trivial in the present sample (as noted by Borenstein, 2009). For simplicity, the standardized mean difference was used for all subsequent analyses.

When both pretest and posttest data were available, posttest effect sizes were adjusted by computing the "difference in differences" in the means from posttest to pretest and standardizing this mean difference by the pooled post-test standard deviation (Borenstein, 2009; Lipsey & Wilson, 2001). Finally, some studies in the sample provided statistics other than means and standard deviations, such as dichotomous proportions (e.g., the percentage of students mastering a skill), focused F tests (e.g., only two groups being compared), t tests, and correlation coefficients (between an outcome and treatment membership). Standard statistical formulas were used to convert these scores to the equivalent standardized mean difference effect size (Lipsey & Wilson, 2001).

3.6.2 *Clustering Effects and Dependent Variable Relationship*

Two adjustments were made to address clustering effects and the relationship between the dependent variables (achievement and orientation): a design effect (Higgins, Eldridge, & Li, 2019; Kish, 1965) and multi-level multivariate meta-analysis (MLMM) modeling (Kalaian &

Kasim, 2008). For many research questions posed in educational contexts, student-level data violate the assumption of statistical independence because they are assigned into treatment groups as a whole class (i.e., cluster assignment) rather than as individuals. The nesting of students within studies in the context of a meta-analysis also violates the assumption of statistical independence. Ignoring these sources of dependence can result in effect sizes that have spuriously small standard errors, meaning such studies will overstate the statistical significance of the tests, and any confidence intervals generated will be too small if not adjusted (Hedges, 2007).

Design-effect-adjusted effect size estimates were computed using Equation 15 from Hedges (2007). Adjusted variances were computed using Equation 16 from Hedges (2007). Hedges and Hedberg (2007) provided estimates of ρ for Grades K–12. For studies involving multiple grades, an average of ρ for the included grades was used.

MLMM modeling was used to adjust effect size estimates for the nesting of students within studies and the covariance between achievement and orientation (Kalaian & Kasim, 2008). Variance between students within a single study (within-study variance) is computed from data in the study and included in the model (V-Known Models), which means that effects and comparisons are based on between-study variance (Raudenbush & Bryk, 2002). MLMM analyses were computed using R 3.6.2 Metafor package (R Core Team, 2019; Viechtbauer, 2010). See Online Supplement A for details about the design effect and MLMM models.

3.6.3 *Publication Bias*

Publication bias occurs as a result of studies not being published because they lack statistical significance in their primary outcomes (Rothstein et al., 2006). In some cases, authors decide not to submit the paper for publication or take longer to do so (Cooper, DeNeve, &

Charlton, 1997; Suñé, Suñé, & Montoro, 2013); in other cases, studies are rejected because they did not report significant findings. Sometimes studies omit information about some outcomes in the study to facilitate publication (*outcome reporting bias*, as in Pigott, Valentine, Polanin, Williams, & Canada, 2013). These actions result in the body of literature available for a meta-analysis having artificially inflated effect sizes.

Methods for adjusting for publication bias are generally not robust in the presence of high heterogeneity (Carter et al., 2019; Stanley, 2017), which we found in the data (see Online Supplement A). Publication bias analyses are based on a set of assumptions about the mechanisms leading to bias; to the extent those assumptions are correct, the models produce more valid results (Vevea, Coburn, & Sutton, 2019). Publication bias tests generally rely on an examination of the relationship between the effect size and its standard error (or variance for some tests), which may be due to publication bias or several other potential explanations (e.g., power analysis, adaptive sampling, repeated trials, and the multifactorial nature of larger studies (i.e., inclusion of moderating factors) yielding smaller effects (Kühberger, Fritz, & Scherndi, 2014). Publication bias is, however, most often the culprit when the effect and its standard error are negatively correlated (Kühberger et al., 2014).

In the present study, 98 of 123 studies (80%) were found in grey literature (dissertations, master's theses, or technical reports). Publication bias in the remaining 20%, however, could still produce bias in the effects (Stanley, 2017). See Online Supplement A Tables A11 and A12 for comparisons of publication type.

To analyze the potential of publication bias, multiple tests were conducted, following the advice of Vevea et al. (2019) to provide triangulation of results. Non-parametric rank correlations between effect sizes and standard errors were computed (Begg & Mezumdar, 1994), and a moderator test between published and unpublished studies was conducted. The Henmi and Copas (2010), Vevea and Woods (2005), and Precision Effect Test-Precision Effect Estimate with Standard Errors (PET-PEESE; Stanley, 2017) models are presented in the results. Additional results from Duval and Tweedie (2000) trim and fill model, Egger, Smith, and Minder (1997) regression test, and Rosenthal-Orwin-Rosenberg fail-safe N tests (Rosenthal, 1979; Orwin, 1983; Rosenberg, 2005) are included in Online Supplement B. For consistency, all publication bias analyses reported in Section 4 are based on design-effect-adjusted effect sizes because some publication bias tests are sensitive to clustering effects. For comparison purposes, analyses based on original effect sizes are included in Online Supplement B.

3.6.4 *Conceptual Emphasis Computation*

All included studies were examined independently by two researchers to compute a conceptual emphasis score. For each study, the achievement items were examined to determine whether procedural or conceptual knowledge was measured. The conceptual emphasis score was the percentage of achievement items that measured conceptual knowledge. The primary coder examined every item for every measure that was reported in the study. Ninety-eight of the studies (79.7%) provided sufficient information to make this determination; 15 of the studies (12.2%) did not share the instrument but were clearly measuring procedural knowledge; 10 studies (8.1%) were unclear and were assumed to be procedural because no claims of conceptual understanding were made. The percentage of items that were judged to address conceptual knowledge was then computed. The secondary coder reviewed those determinations and noted any discrepancies, agreements, disagreements, and questions. The reviewers met and reached consensus for all final scores.

4. Results

This study examined two research questions: (1) what are the effects on achievement and orientation after accounting for dependent variable correlation, clustering effects, and publication bias? and (2) to what extent was conceptual understanding an emphasis of mathematics education technology research? For Question 1, results from the multi-level multivariate meta-analysis (MLMM) model are presented, followed by publication bias analysis results. For Question 2, results from the conceptual emphasis analysis are presented.

All studies in the sample included a control group, but the detail with which the control group was defined varied greatly from study to study. Most studies defined the control group as some sort of "business as usual." The meaning of business as usual was highly variable between studies. Studies also inconsistently described the pedagogy accompanying the technology in the experimental group or in the control group.

4.1 Achievement and Orientation Effect Sizes

The MLMM model produced estimates of the effect size for achievement and orientation after accounting for their correlation and clustering effects. An analysis of true between-study variance based on the MLMM model provides insight into the potential for moderator variables to explain achievement and orientation effects. Publication bias analyses provide estimates of the degree of publication bias in the sample and estimates of the effect sizes after accounting for that bias.

4.1.1 *Achievement and Orientation Effect Sizes after Accounting for their Correlation and Clustering Effects*

The achievement and orientation effect size estimates (Research Question 1) from the MLMM unconditional model based on design-effect-adjusted effect sizes, which accounted for clustering effects were $\gamma_{\mathrm{Ach}} = 0.113$ ($p = .004$), $\gamma_{\mathrm{Orntn}} = 0.125$ ($p < .001$). Although the correlation between achievement and orientation effects was positive and significant before accounting for clustering effects (*rho* = .523, $p < .001$; see Online Supplement B Table B2), the correlation after accounting for clustering was non-significant, *rho* = -.063, $p = .495$. A breakdown of orientation constructs and their effect sizes is provided in Online Supplement C.

The between-study variance (τ) was reduced to zero for both achievement and orientation using the design-effect-adjusted estimates (see Online Supplement B Table B2). Because significant true heterogeneity was not present after accounting for clustering effects, no moderators were added to the model. Moderator tests for unadjusted estimates are provided in Online Supplement A but should be interpreted with caution.

4.1.2 *Influence of Publication Bias on Effect Sizes*

The weighted average achievement effect size for published studies was 0.085 (SE = 0.035) and for unpublished studies was 0.121 (SE = 0.020). For orientation, the weighted average effect size for published studies was 0.208 (SE = 0.035) and for unpublished studies was 0.091 (SE = 0.020). The moderator test for achievement showed no significant variance between published and unpublished studies, $Q_{ach}(df = 1) = 1.3569$, $p = .244$, but there was significant variance for orientation, $Q_{orntn}(df = 1) = 5.5921$, $p = 0.018$.

Begg and Mezumdar (1994) rank correlations between effect size and standard error were not significant for achievement (Kendall's $\tau = 0.0622$, $p = .309$) but were for orientation. (Kendall's $\tau = 0.1689$, $p = 0.006$). This result is consistent with Egger's regression test (Online Supplement B).

The Henmi and Copas (2010) adjusted estimate showed no difference from the design-effect-adjusted estimate (0.113, $p = .004$). The orientation estimate also showed no difference (0.125, $p < .001$). These estimates suggest that whatever publication bias exists in the sample is not responsible for the positive effects that were found.

For the Vevea and Woods (2005) selection model, three sets of weights were analyzed to specify potential effects from different degrees of bias severity (Table 1). Weights to specify more or less severe bias were taken from Vevea et al. (2019).

Table 1

Estimates for Vevea and Woods (2005) Weight Function Selection Models

Model	*p*-value steps	Weights	Intercept estimate
Achievement			
Unadjusted			0.1131
Less bias	.01, .05, .50, 1	1, .90, .70, .50	0.0456
Moderate bias	.01, .05, .10, .50, 1	1, .99, .95, .75, .50	0.0281
Severe bias	.01, .05, .10, .50, 1	1, .99, .90, .50, .10	-0.1926
Orientation			
Unadjusted			0.1247
Less bias	.01, .05, .50, 1	1, .90, .70, .50	0.0568
Moderate bias	.01, .05, .10, .50, 1	1, .99, .95, .75, .50	0.0393
Severe bias	.01, .05, .10, .50, 1	1, .99, .90, .50, .10	-0.1601

Note. Weights are listed respectively to the *p*-value steps.

The adjusted estimates are small for less or moderate bias for both achievement and orientation effects. Only under severe bias do the results indicate a large adjustment.

PET-PEESE meta-regression models were computed using a random effects model to test the null hypothesis that the effect in infinitely large studies is zero with statistical significance indicating that the null hypothesis should be rejected and that a real effect does exist (Table 2).

Table 2
Results for PET-PEESE Models

Model	Estimate	z
Achievement		
PET		
Intercept	0.047 (SE = 0.089)	0.530
SE	0.168 (SE = 0.205)	0.818
PEESE		
Intercept	0.074 (SE = 0.056)	1.320
Variance	0.208 (SE = 0.209)	0.993
Orientation		
PET		
Intercept	-0.070 (SE = 0.090)	-0.781
SE	0.497 (SE = 0.206)	2.410*
PEESE		
Intercept	0.024 (SE = 0.056)	0.425
Variance	0.530 (SE = 0.210)	2.521*

*$p < .05$.

For both achievement and orientation, the PET estimate of the intercept was non-significant, so the PET model was retained. The final models for both achievement and orientation indicated no significant true effect.

Overall, we concluded that the potential for bias is higher in orientation than for achievement. Both effects, however, showed adjustment to near zero in the estimates. Caution should therefore be taken in interpreting effect size estimates as true effects.

4.2 Conceptual Emphasis in Mathematics Education Technology Research

The conceptual emphasis of the technology interventions provides important insight into the way technology has been coupled with pedagogy over time (Research Question 2). No studies focused exclusively on concepts, but 101 studies (82% of 123 studies) did focus exclusively on procedural measures (0% conceptual emphasis). The achievement effect size varied widely across these 101 studies, ranging from -1.37 to 2.67 (weighted average ES = 0.149). The orientation effect size also varied widely, ranging from -0.693 to 3.07 (weighted average ES = 169). The 22 studies (18% of 123 studies) that did include measures of conceptual understanding ranged from 5% to 88% in conceptual emphasis. For these 22 studies, the achievement effect size also varied widely, ranging from -0.285 to 0.659 (weighted average ES = 0.070). For orientation, the effect size ranged from -0.194 to 1.226 (weighted average ES = 0.092). Only two studies used measures that focused at least 50% on concepts (Bouck & Bouck, 2008; Santiago-Collazo, 1995). With so few studies giving meaningful emphasis to concepts, comparisons of the effect sizes were not deemed meaningful; that is, most studies that addressed concepts did so only slightly, so the underlying pedagogy that accompanied the use of the technology was not meaningfully different than the 101 studies with no conceptual emphasis. The emphasis on conceptual understanding did not increase for the studies in the sample over time (Figure 3).

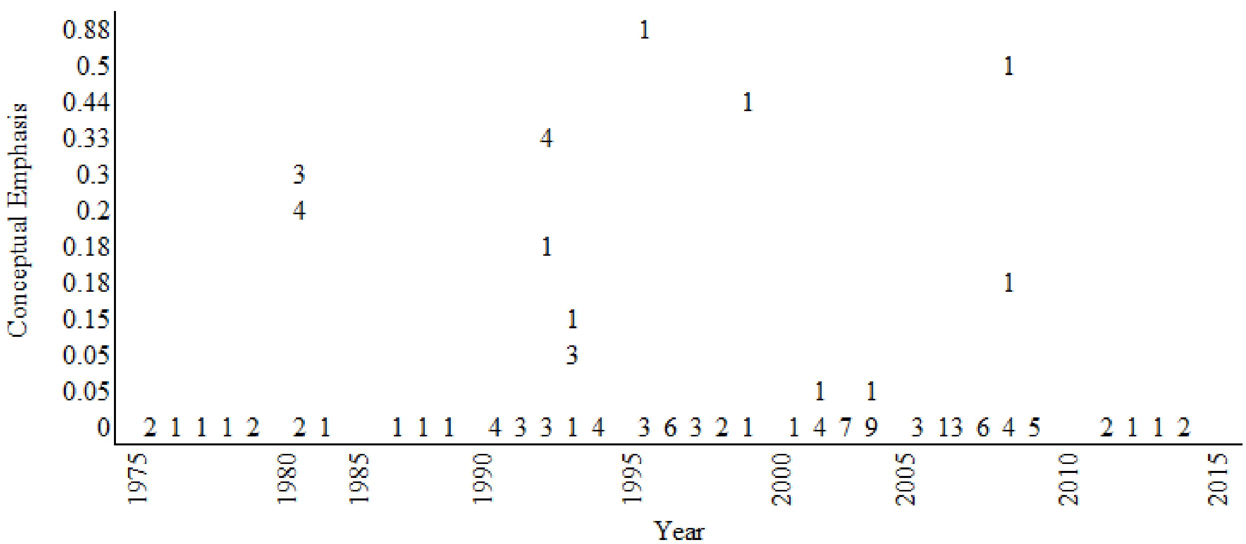

Figure 3. Scatterplot of conceptual understanding emphasis over time. Numbers in the graph represent the number of effect sizes in the same year with the same conceptual emphasis.

The correlation between time and conceptual emphasis was small but significant, $r = -.226$ (SE = 0.089), $p = .012$. This correlation accounted for approximately 5% of the variance in conceptual emphasis. This trend of reducing conceptual emphasis can also be seen by aggregating studies into decades (Table 3) with the highest emphasis on conceptual understanding between 1980 and 1989.

Table 3

Conceptual Emphasis by Decade

Decade	Mean Percent Conceptual Emphasis	Percent of Studies with Conceptual Emphasis > 0	Number of Studies
1970-1979	0.0	0.0	7
1980-1989	13.1	53.8	13
1990-1999	7.6	26.8	41
2000-2009	1.4	7.1	56
2010-2014	0.0	0.0	6

Note. Total N = 123 studies.

Table 4 provides the mean conceptual emphasis by each type of technology use in the intervention. This comparison addresses Research Question 2 (conceptual emphasis of mathematics education technology research) for both pedagogy and assessment. Effect sizes by technology use are provided in Online Supplement A.

Table 4

Technology Use by Conceptual Emphasis

Technology Use	Mean Conceptual Emphasis (SD)	Number of Studies
Instruction Enhancement	7.1% (0.16)	45
Computation	4.1% (0.10)	42
Active Learning	0.0% (0.00)	20
Tutorial	0.0% (0.00)	9
Assessment	12.5% (0.25)	4
Technology-rich environment; Uses not specified	6.0% (0.10)	3

Note. Total N = 123 studies.

5. Discussion

This section will discuss the results in terms of general conclusions, control conditions, and conceptual emphasis. The discussion will conclude with recommendations for future research.

5.1 General Conclusions

Overall, we concluded that the evidence is insufficient to make claims about technology's general effectiveness in supporting mathematics learning outcomes. The effect sizes for achievement and orientation after adjusting for clustering effects were very small but statistically significant. Adjustments for publication bias reduced them to zero. Clustering effect adjustments also reduced model variance to zero, which means that no features of participants, type of training, or other potential moderating variables can improve or explain intervention effects in this sample of studies.

5.2 Control Conditions

Control group conditions are especially important because they help define the nature of the intervention, the independent variable, and how to interpret the results. Seventy studies were excluded because of lack of a control group, 31 of which had a control group for achievement but not for orientation. In the sample studies, control group conditions were described in very general terms, leaving the nature of the independent variable in doubt. Most studies described some form of "business as usual" condition. In some studies, business as usual meant the same pedagogy in both groups with and without technology. But in other studies, the technology innovation effected a different pedagogical approach that was not clearly accounted for in the control group. Many descriptions were unclear about the nature of the pedagogy in the treatment and control groups. This lack of clarity warrants caution in interpreting effects from these studies.

5.3 Conceptual Emphasis

The exploration of conceptual emphasis found that most studies (82%) focused entirely on procedural understanding, and that focus has not changed over time. The 20 active learning studies included no conceptual emphasis in their achievement measures. This result was surprising given the exploratory, conceptual nature of active learning pedagogies.

Most technology can support procedural or conceptual understanding, depending on how it is used. For example, a four-function calculator can be used to simply check answers (as in

Godia, 1982), or it can be used to recognize number patterns and develop mathematical reasoning about those patterns (e.g., broken calculator activities, as in Leatham, Lawrence, & Mewborn, 2005). Some technology tools have been developed with the explicit purpose of fostering conceptual understanding (e.g., understanding equivalence of fractions applet at the National Library of Virtual Manipulatives, 2017). While the advent of technology offers ripe opportunities for exploratory learning to help students build connections, the present study found that most research efforts in mathematics education technology have largely neglected to move beyond skill-based outcomes.

5.4 Recommendations

This study found a lack of information in the sample studies regarding the way pedagogy and technology were integrated and the nature of the control conditions. We therefore recommend that future studies of mathematics education technology examine both the pedagogy and the technology and describe the control conditions more fully. Because most studies measured achievement wholly through procedural skills, we recommend that future research include conceptual measures. Furthermore, we recommend that outcomes beyond achievement be given more attention in research designs to fully explore the complex array of student outcomes in a learning situation.

References

Abramowitz, S. K. (1999). *A computer-enhanced course in descriptive statistics at the college level: An analysis of student achievement and attitudes* (Doctoral dissertation). Dissertation Abstracts International (DAI)-A, 60/09. UMI No. 9946935

Aiken, L. R. (1970). Attitudes toward mathematics. *Review of Educational Research, 40,* 551-596. https://doi.org/10.3102/00346543040004551

Aiken, L. R. (1976). Update on attitudes and other affective variables in learning mathematics. *Review of Educational Research, 46,* 293-311.

Bai, H., Pan, W., Hirumi, A., & Kebritchi, M. (2012). Assessing the effectiveness of a 3-D instructional game on improving mathematics achievement and motivation of middle school students. *British Journal of Educational Technology, 43,* 993-1003.

Baki, A., & Guven, B. (2009). Khayyam with Cabri: Experiences of pre-service mathematics teachers with Khayyam's solution of cubic equations in dynamic geometry environment. *Teaching Mathematics and Its Applications, 28*, 1-9.

Begg, C. B., & Mazumdar, M. (1994). Operating characteristics of a rank correlation test for publication bias. Biometrics, 50, 1088–1101.

Bolin, B. (1992). *Assessment of the effect of a technologically-rich environment on the mathematics and science achievement of secondary school students and on their attitudes toward technology* (Doctoral dissertation). DAI-A, 53/06. UMI No. 9232478.

Borenstein, M. (2009). Effect sizes for continuous data. In H. Cooper, L. V. Hedges, & J. C. Valentine, *The handbook of research synthesis and meta-analysis* (pp. 221-235). New York, NY: Russell Sage Foundation.

Bouck, E. C., & Bouck, M. K. (2008). Does it add up? Calculators as accommodations for sixth grade students with disabilities. *Journal of Special Education Technology, 23*, 17-32.

Boutron, I., Page, M. J., Higgins, J. P. T., Altman, D. G., & Lundh, A., & Hróbjartsson, A. (2019). Considering bias and conflicts of interest among the included studies. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch (Eds.), *Cochrane Handbook for Systematic Reviews of Interventions Version 6.0* (Ch. 7). Chichester, UK: Cochrane Collaborative, Cochrane Bias Methods Group. Available from https://training.cochrane.org/handbook/current/chapter-07

Brewer, D. S. (2009). *The effects of online homework on achievement and self-efficacy of college algebra students* (Doctoral dissertation). DAI-A 70/07. UMI No. 3366157.

Brown, S. E. (2007). *Counting Blocks or Keyboards? A Comparative Analysis of Concrete versus Virtual Manipulatives in Elementary School Mathematics Concepts* (Unpublished master's thesis). Marygrove College, Detroit, MI. Retrieved from https://eric.ed.gov/?id=ED499231

Brownell, W. A. (1935). Psychological considerations in the learning and teaching of arithmetic. In W. D. Reeve (Ed.), *The teaching of arithmetic: Tenth yearbook of the National Council of Teachers of Mathematics* (pp. 1-31). New York, NY: Teachers College, Columbia University.

Campuzano, L., Dynarski, M., Agodini, R., & Rall, K. (2009). *Effectiveness of reading and mathematics software products: Findings from two student cohorts* (NCEE 2009-4041). Washington, DC: Institute of Education Sciences, National Center for Education Evaluation and Research. https://ies.ed.gov/ncee/pubs/20094041/pdf/20094041.pdf

Carter, E. C., Schönbrodt, F. D., Gervais, W. M., & Hilgard, J. (2019). Correcting for bias in psychology: A comparison of meta-analytic methods. *Advances in Methods and*

Practices in Psychological Science, 2, 115-144. doi:10.1177/2515245919847196

Chen, C. J. (2005). *Learning mathematics problem solving through personalized computer-assisted program in Taiwan* (Doctoral dissertation). DAI-A, 66/11. UMI No. 3196789

Chen, C. (2008). *The effectiveness of computer supported collaborative learning on helping tasks in a mathematics course.* Dissertation Abstracts International-A, 69/09, Dissertation Number 3325233.

Clark, R. E. (1983). Reconsidering research on learning from media. *Review of Educational Research, 53*, 445-459.

Clark, R. E. (1994). Media will never influence learning. *Educational Technology Research and Development, 42*, 21-29.

Cohen, J., & Hollebrands, K. F. (2011). Technology tools to support mathematics teaching." In T. P. Dick & K. F. Hollebrands (Eds.), *Focus in High School Mathematics: Technology to Support Reasoning and Sense Making* (pp. 105–22). Reston, VA: National Council of Teachers of Mathematics.

Conn, V. S., Valentine, J. C., Cooper, H. M., & Rantz, M. J. (2003). Grey literature in meta-analyses. *Nursing Research, 52*, 256-261.

Cooper, H., DeNeve, K., & Charlton, K. (1997). Finding the missing science: The fate of studies submitted for review by a human subjects committee. *Psychological Methods, 2*, 447–452. doi:10.1037//1082-989X.2.4.447

Cooper, H., Hedges, L. V., & Valentine, J. C. (2009). *The handbook of research synthesis and meta-analysis* (2nd ed.). New York, NY: Russell Sage Foundation.

Corbin, J., & Strauss, A. (2008). *Basics of qualitative research* (3 ed.). Thousand Oaks, CA: SAGE.

Creswell, J. W., & Plano Clark, V. L. (2007). *Designing and conducting mixed methods research.* Thousand Oaks, CA: Sage.

Dick, T. P., & Hollebrands, K. F. (2011). *Focus in High School Mathematics: Technology to support reasoning and sense making.* Reston, VA: National Council of Teachers of Mathematics.

Duffy, J. A., & Thompson, G. E. (1980). *Improving mathematics achievement of elementary students through the use of electronic hand calculators*. Columbus, OH: Columbus Public Schools. Retrieved from https://eric.ed.gov/?id=ED209263

Duval, S., & Tweedie, R. (2000). Trim and fill: A simple funnel-plot-based method of testing and adjusting for publication bias in meta-analysis. *Biometrics, 56*, 455-463.

Egger, M., Smith, G. D., & Minder C. (1997). Bias in meta-analysis detected by a simple, graphical test. *British Medical Journal, 315* (7109), 629. doi:dx.doi.org/10.1136/bmj.315.7109.629

Ellerman, T. B. (1998). *A study of calculator usage on the mathematics achievement of seventh- and eighth-grade students and on attitudes of students and teachers* (Doctoral dissertation). DAI-A, 59/04. UMI No. 9829094

Ellington, A. J. (2000). *Effects of hand-held calculators on precollege students in mathematics classes—A meta-analysis* (Doctoral dissertation). DAI 61/11. UMI No. 9996347.

Ellington, A. J. (2003). A meta-analysis of the effects of calculators on students' achievement and attitude levels in precollege mathematics classes. *Journal for Research in Mathematics Education, 34*, 433-463.

Ellington, A. J. (2006). The effects of non-CAS graphing calculators on student achievement and attitude levels in mathematics: A meta-analysis. *School Science & Mathematics, 106*, 16-

26.

Erlwanger, S. H. (2004). Benny's conception of rules and answers in IPI mathematics. In T. P. Carpenter, J. A. Dossey, & J. L. Koehler (Eds.), *Classics in Mathematics Education Research* (pp. 48–58). Reston, VA: National Council of Teachers of Mathematics.

Ersoy, M. & Akbulut, Y. (2014). Cognitive and affective implications of persuasive technology use on mathematics instruction. *Computers & Education, 75,* 253-262.

Feliciano, B. (1996). *The effect of computer use on mathematical reasoning, problem-solving skills and attitudes at the college level* (Doctoral dissertation). DAI-A, 57/07. UMI No. 9635971

Fennema, E., & Sherman, J. (1976). Fennema-Sherman mathematics attitude scales: Instruments designed to measure attitudes toward the learning of mathematics by males and females. *Journal for Research in Mathematics Education, 7*, 324-326.

Fletcher, J. D., Hawley, D. E., & Piele, P.K. (1990). Costs, effects, and utility of microcomputer-assisted instruction in the classroom. *American Educational Research Journal, 27*, 783-806.

Fox, L. F. (1998). *The effect of a graphing calculator used in an active learning environment on intermediate algebra students' achievement and attitude* (Doctoral dissertation). DAI-A, 59/03. UMI No. 9827825

Galbraith, P., & Haines, C. (1998). Disentangling the nexus: Attitudes to mathematics and technology in a computer learning environment. *Educational Studies in Mathematics, 36*, 275-290.

Godia, G. I. (1982). *A comparative study of the effects on achievement, changes in attitude toward mathematics and attrition rate of students enrolled in the freshman remedial* *arithmetic course under two different instructional approaches* (Doctoral dissertation). DAI-A, 42/08. UMI No. 8201446

Goodwin, B., & Miller, K. (2013). Evidence on flipped classrooms is still coming in. *Educational Leadership, 70*, 78–80.

Grbich, C. (2007). *Qualitative data analysis: An introduction*. Thousand Oaks, CA: Sage.

Harter, C. A. (2006). *The effects of spatial contiguity within computer-based instruction of group personalized two-step mathematics word problems* (Doctoral dissertation). DAI-A, 68/10. UMI No. 3286363

Hedges, L. V. (2007). Effect sizes in cluster-randomized designs. *Journal of Educational and Behavioral Statistics, 32*, 341-370. doi:10.3102/1076998606298043

Hedges, L. V., & Hedberg, E. C. (2007). Intraclass correlation values for planning group randomized trials in education. *Educational Evaluation and Policy Analysis, 29*, 60-87. doi:10.3102/0162373707299706

Hembree, R., & Dessart, D. J. (1986). Effects of hand-held calculators in precollege mathematics education: A meta-analysis. *Journal for Research in Mathematics Education, 17*, 83-99.

Henmi, M., & Copas, J. B. (2010). Confidence intervals for random effects meta-analysis and robustness to publication bias. *Statistics in Medicine, 29*, 2969–2983. doi:10.1002/sim.4029

Hiebert, J., & Grouws, D. A. (2007). The effects of classroom mathematics teaching on students' learning. In F. K. Lester (Ed.), *Second handbook of research on mathematics teaching and learning* (pp. 371-404). Reston, VA: National Council of Teachers of Mathematics.

Higgins, J. P. T., Eldridge, S., & Li, T. (2019). Including variants on randomized trials. In J. P. T. Higgins, J. Thomas, J. Chandler, M. Cumpston, T. Li, M. J. Page, & V. A. Welch

(Eds.), *Cochrane Handbook for Systematic Reviews of Interventions Version 6.0* (Ch. 23). Chichester, UK: Cochrane Collaborative, Cochrane Bias Methods Group. Available from https://training.cochrane.org/handbook/current/chapter-23

Hodanbosi, C. L. (2001). *A comparison of the effects of using a dynamic geometry software program and construction tools on learner achievement* (Doctoral dissertation). DAI-A, 63/02. UMI No. 3042388

Hoffman, B. (2010). "I think I can, but I'm afraid to try": The role of self-efficacy beliefs and mathematics anxiety in mathematics problem-solving efficiency. *Learning & Individual Differences, 20*, 276-283.

Hurn, J. L. (2006). *An analysis of the effects of online practice quizzes on the achievement, self-efficacy, and academic motivation of college algebra students at a community college* (Doctoral dissertation). DAI-A, 67/06. UMI No. 3223374

Hylton-Lindsay, A. A. (1997). *The effect of the graphing calculator on metacognitive aspects of student performance in precalculus for business* (Doctoral dissertation). DAI-A, 58/09. UMI No. 9810960

Isiksal, M., & Askar, P. (2005). The effect of spreadsheet and dynamic geometry software on the achievement and self-efficacy of 7th-grade students. *Educational Research, 47,* 333-350.

Kalaian, S. A., & Kasim, R. M. (2008). Multilevel methods for meta-analysis. In A. A. O'Connell & D. B. McCoach (Eds.), *Multilevel modeling of educational data* (pp. 315-345). Charlotte, NC: Information Age Publishing.

Kaput, J., Hegedus, S., & Lesh, R. (2007). Technology becoming infrastructural in mathematics education. In R. Lesh, E. Hamilton, & J. Kaput (Eds*.), Foundations for the future in mathematics education* (pp. 173–192). Mahwah, NJ: Lawrence Erlbaum.

Ke, F. (2006). *Computer-based game playing within alternative classroom goal structures on fifth-graders' math learning outcomes: Cognitive, metacognitive, and affective evaluation and interpretation* (Doctoral dissertation). DAI-A, 67/08. UMI No. 3229015

Kim, C. (2007). *Effects of motivation, volition, and belief change strategies on attitudes, study habits, and achievement in mathematics education* (Doctoral dissertation). DAI-A, 69/02. UMI No. 3301566

Kish, L. (1965). *Survey sampling*. New York: John Wiley & Sons.

Kühberger, A., Fritz, A., & Scherni, T. (2014). Publication bias in psychology: A diagnosis based on the correlation between effect size and sample size. *PLOS ONE, 9*(9): e105825. doi:10.1371/journal.pone.0105825

Leatham, K. R., Lawrence, K., & Mewborn, D. S. (2005). Getting started with open-ended assessment. *Teaching Children Mathematics, 11*, 413-419.

Li, Q., & Ma, X. (2010). A meta-analysis of the effects of computer technology on school students' mathematics learning. *Educational Psychology Review, 22*, 215-243.

Linn, R., Bond, L., Carr, P., Darling-Hammond, L., Harris, D., Hess, F., & Shulman, L. (2013). *Student learning, student achievement: How do teachers measure up?* Alexandria, VA: National Board for Professional Teaching Standards.

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Thousand Oaks, CA: Sage.

Ma, X. (1999). A meta-analysis of the relationship between anxiety toward mathematics and achievement in mathematics. *Journal for Research in Mathematics Education, 30*, 520-540.

May, P. L. (2005). *Analysis of computer algebra system tutorials using cognitive load theory* (Doctoral dissertation). DAI-A, 66/05. UMI No. 3177549.

Mirick, J. L. (2002). *Benefits of a calculator tutorial in a college algebra classroom* (Doctoral dissertation). DAI-A, 63/11. UMI No. 3017560.

Moher D., Liberati A., Tetzlaff J., Altman D. G., & PRISMA Group (2009). Preferred reporting items for systematic reviews and meta-Analyses: The PRISMA statement. *PLoS Med 6*(7): e1000097. doi:10.1371/journal.pmed1000097

National Council of Teachers of Mathematics. (1989). *Curriculum and evaluation standards for school mathematics*. Reston, VA: Author.

National Council of Teachers of Mathematics. (2000). *Principles and standards of school mathematics*. Reston, VA: Author.

National Council of Teachers of Mathematics. (2014). *Principles to actions: Ensuring mathematical success for all.* Reston, VA: Author.

National Library of Virtual Manipulatives. (2017). *Fractions-equivalent applet*. [website]. Logan, UT: Utah State University. http://nlvm.usu.edu/en/nav/frames_asid_105_g_4_t_1.html?from=category_g_4_t_1.html

Neale, D. C. (1969). The role of attitudes in learning mathematics. *Arithmetic Teacher, 8*, 631-640.

Ogbuehi, P. L., & Fraser, B. J. (2007). Learning environment, attitudes and conceptual development associated with innovative strategies in middle-school mathematics. *Learning Environments Research, 10*, 101-114.

Orwin, R. G. (1983). A fail-safe N for effect size in meta-analysis. *Journal of Educational Statistics, 8,* 157–159.

Philipp, R. A., Ambrose, R., Lamb, L. L. C., Sowder, J. T., Schappelle, B. P., Sowder, L. et al. (2007). Effects of early field experiences on the mathematical content knowledge and beliefs of prospective elementary school teachers: An experimental study. *Journal for Research in Mathematics Education, 38,* 438-476.

Pigott, T. D., Valentine, J. C., Polanin, J. R., Williams, R. T., & Canada, D. D. (2013). Outcome-reporting bias in education research. *Educational Researcher, 42*, 424-432. doi: 10.3102/0013189X13507104

Pilli, O., & Aksu, M. (2013). The effects of computer-assisted instruction on the achievement, attitudes and retention of fourth grade mathematics students in North Cyprus. *Computers & Education, 62,* 62-71.

Plourde, J. (2008). *The effect of inquiry-based, hands-on math instruction utilized in combination with web-based, computer-assisted math instruction on 4th-grade students' outcomes* (Doctoral dissertation). DAI-A 69/09. UMI No. 3324659.

R Core Team. (2019). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Ronau, R. N., Rakes, C. R., Bush, S., Driskell, S., Niess, M. L., & Pugalee, D. (2014). A survey of mathematics educational technology dissertation scope and quality: 1968-2009. *American Educational Research Journal, 51*, 974-1006. doi:10.3102/0002831214531813.

Ronau, R. N., Rakes, C. R., Niess, M. L., Bush, S. B., Driskell, S., & Pugalee, D. (2015). The quality of mathematics education technology literature. *Journal of Multidisciplinary Evaluation, 11*, 12-36. http://journals.sfu.ca/jmde/index.php/jmde_1/article/view/397/396

Roschelle, J., Pea, R., Hoadley, C., Gordin, D., & Means, B. (2000). Changing how and what children learn in school with computer-based technologies. *The Future of Children, 10*(2), 76–101.

Roschelle, J., Shechtman, N., Tatar, D., Hegedus, S., Hopkins, B., Empson, S., Knudsen, J., & Gallagher, L. P. (2010). Integration of technology, curriculum, and professional development for advancing middle school mathematics: Three large-scale studies. *American Educational Research Journal, 47*, 833–78.

Rosenberg, M. S. (2005). The file-drawer problem revisited: A general weighted method for calculating fail-safe numbers in meta-analysis. *Evolution, 59*, 464–468.

Rosenthal, R. (1979). The "file drawer problem" and tolerance for null results. *Psychological Bulletin, 86*, 638–641.

Ross, J. A., Bruce, C. D., & Sibbald, T. M. (2011). Sequencing computer-assisted learning of transformations of trigonometric functions. *Teaching Mathematics & its Applications, 30,* 120-137.

Rothstein, H. R., & Hopewell, S. (2009). Grey literature. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The Handbook of Research Synthesis and Meta-Analysis* (pp. 103-126). New York, NY: Russell Sage Foundation.

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (2006). *Publication bias in meta-analysis: Prevention, assessment and adjustments.* Chichester, England: John Wiley & Sons.

Santiago-Collazo, D. (1995). *The effects of the use of a Logo computer experience on geometry problem-solving for Hispanic limited English proficient migrant elementary students* (Doctoral dissertation). DAI-A, 56/05. UMI No. 9532017

Schoenfeld, A. H. (1982, March). *Beyond the purely cognitive: Metacognition and social cognition as driving forces in intellectual performance.* Paper presented at the annual meeting of the American Educational Research Association, New York.

Schoenfeld, A. H. (1985, April). *Students' beliefs about mathematics and their effects on mathematical performance: A questionnaire analysis.* Paper presented at the annual meeting of the American Educational Research Association, Chicago, IL.

Schoenfeld, A. H. (1989). Explorations of students' mathematical beliefs and behavior. *Journal for Research in Mathematics Education*, 20, 338-355.

Schoenfeld, A. H. (2011). *How we think: A theory of goal-oriented decision making and its educational applications.* New York, NY: Routledge.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston, MA: Houghton Mifflin.

Shulman, L. S., & Wilson, S. M. (2004). *The wisdom of practice: Essays on teaching, learning, and learning to teach.* San Francisco: Jossey-Bass.

Sickel, J. L. (2019). The great media debate and TPACK: A multidisciplinary examination of the role of technology in teaching and learning. *Journal of Research on Technology in Education, 51*, 152-165. doi: 10.1080/15391523.2018.1564895

Smith, K. B. (1991). *An integration of the computer algebra system DERIVE into instruction of linear programming* (Doctoral dissertation). DAI-A, 52/10. UMI No. 9200846

Song, F., Hooper, L., & Loke, Y. K. (2013). Publication bias: What is it? How do we measure it? How do we avoid it? *Open Access Journal of Clinical Trials, 5*, 71-81. doi:10.2147/OAJCT.S34419

Spence, D. J. (2004). *Engagement with mathematics courseware in traditional and online learning environments: Relationship to motivation, achievement, gender, and gender orientation* (Doctoral dissertation). DAI-A, 65/02. UMI No. 3123365

Spinelli, M. A. (2001). The use of technology in teaching business statistics. *Journal of Education for Business, 77,* 41-44.

Stanley, T. D. (2017). Limitation of PET-PEESE and other meta-analysis methods. *Social Psychological and Personality Science, 8*, 581-591. doi: 10.1177/1948550617693062

Stigler, J. W., & Hiebert, J. (1997). Understanding and improving classroom mathematics instructions: An overview of the TIMSS video study. *Phi Delta Kappan, 79,* 14-21.

Suñé, P., Suñé, J. M., & Montoro, J. B. (2013). Positive outcomes influence the rate and time to publication, but not the impact factor of publications of clinical trial results. *PLoS One, 8*, 1–8. doi:10.1371/journal.pone.0054583

Tapia, M., & Marsh, G. E. (2004). An instrument to measure mathematics attitudes. *Academic Exchange Quarterly, 8*, 16-21.

Vevea, J. L., Coburn, K., & Sutton, A. (2019). Publication bias. In H. Cooper, L. V. Hedges, & J. C. Valentine (Eds.), *The Handbook of Research Synthesis and Meta-Analysis (3rd. ed.; pp. 383-432)*. New York, NY: Russell Sage Foundation.

Vevea, J. L., & Woods, C.M. (2005). Publication bias in research synthesis: Sensitivity analysis using a priori weight functions. *Psychological Methods, 10*, 428-443. doi: 10.1037/1082-989X.10.4.428

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*, 1–48. http://www.jstatsoft.org/v36/i03/.

Voloshin, D. (2009). *An evaluation of a computer-assisted, remedial algebra curriculum on attitudes and performance of ninth grade English learners* (Doctoral dissertation). DAI-A, 70/07. UMI No. 3367762

Welch, W. (1978). Science education in Urbanville. In R. Stake & J. Easley (Eds.), *Case studies* *in science education* (pp. 5-1-5-33). Urbana: University of Illinois.

Wodarz, N. (1994). *The effects of computer usage on elementary students' attitudes, motivation and achievement in mathematics* (Doctoral dissertation). DAI-A, 55/12. UMI No. 9512915

Yang, K. H. (2014). The WebQuest model effects on mathematics curriculum learning in elementary school students. *Computers & Education, 72,* 158-166.

Zunker, L. J. (2008). *Computer-based instruction and mathematics skills of elementary students with learning disabilities* (Doctoral dissertation). DAI-A, 69/10. UMI No. 3332683

Studies Included in the Meta-Analysis

Abramowitz, S. K. (1999). *A computer-enhanced course in descriptive statistics at the college level: An analysis of student achievement and attitudes* (Doctoral dissertation). DAI-A, 60/09. UMI No. 9946935.

Akinsola, M. K., & Animasahun, I. A. (2007). The effect of simulation-games environment on students achievement in and attitudes to mathematics in secondary schools. *Turkish Online Journal of Educational Technology, 6,* 1-7.

Bai, H., Pan, W., Hirumi, A., & Kebritchi, M. (2012). Assessing the effectiveness of a 3-D instructional game on improving mathematics achievement and motivation of middle school students. *British Journal of Educational Technology, 43,* 993-1003.

Bartos, J. J. (1986). *Mathematics achievement and the use of calculators for middle elementary grade children* (Doctoral dissertation). DAI-A, 47/04. UMI No. 8614912.

Benson, C. T. (1989). *Effect of computer instruction in finite mathematics on student achievement and attitude* (Doctoral dissertation). DAI-A, 60/09. UMI No. 9004078.

Bolin, B. (1992). *Assessment of the effect of a technologically-rich environment on the mathematics and science achievement of secondary school students and on their attitudes toward technology* (Doctoral dissertation). DAI-A, 53/06. UMI No. 9232478.

Bouck, E. C., & Bouck, M. K. (2008). Does it add up? Calculators as accommodations for sixth grade students with disabilities. *Journal of Special Education Technology, 23*, 17-32.

Brekke, D. L. (1991). *The effects of training on teacher attitudes toward calculators and problem-solving and the effects of calculator training on student problem-solving ability and attitude toward mathematics* (Doctoral dissertation). DAI-A, 51/12. UMI No. 9113783.

Brewer, D. S. (2009). *The effects of online homework on achievement and self-efficacy of college algebra students* (Doctoral dissertation). DAI-A 70/07. UMI No. 3366157.

Brown, S. E. (2007). *Counting Blocks or Keyboards? A Comparative Analysis of Concrete versus Virtual Manipulatives in Elementary School Mathematics Concepts* (Unpublished master's thesis). Marygrove College, Detroit, MI. Retrieved from https://eric.ed.gov/?id=ED499231

Buck, L. (2009). *The motivational effects of a GPS mapping project on student attitudes toward mathematics and mathematical achievement* (Doctoral dissertation). DAI-A, 70/05. UMI No. 3356452.

Carter, M. B. (2004). *An analysis and comparison of the effects of computer instruction versus traditional lecture instruction on student attitude and achievement in a college remedial mathematics course* (Doctoral dissertation). DAI -A, 65/04. UMI No. 3128520

Chen, C. J. (2005). *Learning mathematics problem solving through personalized computer-assisted program in Taiwan* (Doctoral dissertation). DAI-A, 66/11. UMI No. 3196789

Connors, M. A. C. (1995). *An analysis of student achievement and attitudes by gender in computer-integrated and non-computer-integrated first year college mainstream calculus courses* (Doctoral dissertation). DAI-A, 57/02. UMI No. 9524690

Costner, B. G. (2002). *The effects on student achievement and attitudes of incorporating a computer algebra system into a remedial college mathematics course* (Doctoral dissertation). DAI-A, 63/07. UMI No. 3059227

Davidson, A. (2004). *An examination of the effects and costs of instruction that relies on computer-assisted instruction for delivering and managing homework assignments in college calculus courses* (Doctoral dissertation). DAI-A, 65/02. UMI No. 3122232

Duffy, J. A., & Thompson, G. E. (1980). *Improving mathematics achievement of elementary students through the use of electronic hand calculators*. Columbus, OH: Columbus Public Schools. Retrieved from https://eric.ed.gov/?id=ED209263

Ellerman, T. B. (1998). *A study of calculator usage on the mathematics achievement of seventh- and eighth-grade students and on attitudes of students and teachers* (Doctoral dissertation). DAI-A, 59/04. UMI No. 9829094

Ellingwood, M. A. R. (1997). *The effects of Logo instruction on the higher-order thinking skills and mathematical achievement of male and female first-grade students* (Doctoral dissertation). DAI-A, 58/01. UMI No. 9719966

Ersoy, M. & Akbulut, Y. (2014). Cognitive and affective implications of persuasive technology use on mathematics instruction. *Computers & Education, 75,* 253-262.

Feliciano, B. (1996). *The effect of computer use on mathematical reasoning, problem-solving skills and attitudes at the college level* (Doctoral dissertation). DAI-A, 57/07. UMI No. 9635971

Fletcher, J. D., Hawley, D. E., & Piele, P.K. (1990). Costs, effects, and utility of microcomputer-assisted instruction in the classroom. *American Educational Research Journal, 27*, 783-806.

Fox, L. F. (1998). *The effect of a graphing calculator used in an active learning environment on intermediate algebra students' achievement and attitude* (Doctoral dissertation). DAI-A, 59/03. UMI No. 9827825

Fredenberg, V. G. (1993). *Supplemental visual computer-assisted instruction and student achievement in freshman college calculus* (Doctoral dissertation). DAI-A, 55/01. UMI No. 9417924

French, D. M. (1997). *A comparison study of computer assisted instruction using interactive software versus traditional instruction in a college precalculus course* (Doctoral dissertation). DAI-A, 58/06. UMI No. 9737941

Funkhouser, C. P. (1990). *The effects of problem-solving software on the problem-solving ability of secondary school students* (Doctoral dissertation). DAI-A, 51/07. UMI No. 9026186

Funkhouser, C. P. (2002). The effects of computer-augmented geometry instruction on student performance and attitudes. *Journal of Research on Technology in Education, 53*, 163-175.

Godia, G. I. (1982). *A comparative study of the effects on achievement, changes in attitude toward mathematics and attrition rate of students enrolled in the freshman remedial arithmetic course under two different instructional approaches* (Doctoral dissertation). DAI-A, 42/08. UMI No. 8201446

Hamlett, C. M. (2006). *Self-directed learning and achievement in a Blackboard-based college algebra course* (Doctoral dissertation). DAI-A, 67/01. UMI No. 3206884

Hamtini, T. M. (2000). *A comparison study of computer-facilitated instruction versus non-computer facilitated instruction in developmental mathematics at a university: Students' attitudes and achievement* (Doctoral dissertation). DAI-A, 61/04. UMI No. 9970119

Harter, C. A. (2006). *The effects of spatial contiguity within computer-based instruction of group personalized two-step mathematics word problems* (Doctoral dissertation). DAI-A, 68/10. UMI No. 3286363

Heath, R. D. (1987). *The effect of calculators and computers on problem-solving ability, computational ability and attitude toward mathematics* (Doctoral dissertation). DAI-A, 48/05. UMI No. 8715286

Her, M. (2006). *An investigation of students' media preferences in learning mathematical concepts* (Doctoral dissertation). DAI-A, 69/09. UMI No. 3332593

Hodanbosi, C. L. (2001). *A comparison of the effects of using a dynamic geometry software program and construction tools on learner achievement* (Doctoral dissertation). DAI-A, 63/02. UMI No. 3042388

Hollar, J. C. (1996). *The effects of a graphing approach college algebra curriculum on students' understanding of the function concept* (Doctoral dissertation). DAI-A, 57/07. UMI No. 9638343

Hopkins, B. L. (1978). *The effect of a hand-held calculator curriculum in selected fundamentals of mathematics classes* (Doctoral dissertation). DAI-A, 39/05. UMI No. 0514761

Hulse, J. W. (1992). *A comparison of the effects of spreadsheet use and traditional methods on student achievement and attitudes in selected collegiate mathematics topics* (Doctoral dissertation). DAI-A, 53/08. UMI No. 9238484

Hunter, R. J. (2004). *The effects of graphing calculator use on students' understanding of functions and graphs in college algebra.* (Master's thesis). MAI, 43/01M. UMI No. 1421202

Hurn, J. L. (2006). *An analysis of the effects of online practice quizzes on the achievement, self-efficacy, and academic motivation of college algebra students at a community college* (Doctoral dissertation). DAI-A, 67/06. UMI No. 3223374

Hutton, L. A. (1977). *The effects of the use of mini-calculators on attitude and achievement in mathematics* (Doctoral dissertation). DAI-A, 37/08. UMI No. 7703347

Hylton-Lindsay, A. A. (1997). *The effect of the graphing calculator on metacognitive aspects of student performance in precalculus for business* (Doctoral dissertation). DAI-A, 58/09.

UMI No. 9810960

Idris, N. (2006). Exploring the effects of TI-84 Plus on achievement and anxiety in mathematics. *Eurasia Journal of Mathematics, Science & Technology Education, 2,* 66-78.

Isiksal, M., & Askar, P. (2005). The effect of spreadsheet and dynamic geometry software on the achievement and self-efficacy of 7th-grade students. *Educational Research, 47,* 333-350.

Jones, E. W. (1976). *The effect of the hand-held calculator on mathematics achievement, attitude and self concept of sixth grade students* (Doctoral dissertation). DAI-A, 37/03. UMI No. 7619885

Jones, L. J. S. (1995). *A comparison of the effects of computer-assisted instruction using Logo and prescription learning on the achievement and attitude of second-grade students* (Doctoral dissertation). DAI-A, 56/09. UMI No. 9601429

Ke, F. (2006). *Computer-based game playing within alternative classroom goal structures on fifth-graders' math learning outcomes: Cognitive, metacognitive, and affective evaluation and interpretation* (Doctoral dissertation). DAI-A, 67/08. UMI No. 3229015

Kebritchi, M. (2008). *Effects of a computer game on mathematics achievement and class motivation: An experimental study* (Doctoral dissertation). DAI-A, 69/06. UMI No. 3319249

Kim, C. (2007). *Effects of motivation, volition, and belief change strategies on attitudes, study habits, and achievement in mathematics education* (Doctoral dissertation). DAI-A, 69/02. UMI No. 3301566

Klein, T. J. (1993). *A comparative study on the effectiveness of differential equations instruction with and without a computer algebra system* (Doctoral dissertation). DAI-A, 54/11. UMI No. 9412432

Ku, H. Y., Harter, C. A., Liu, P. L., Thompson, L., & Cheng, Y. C. (2007). The effects of individually personalized computer-based instructional program on solving mathematics problems. *Computers in Human Behavior, 23*, 1195-1210.

Lim, C. Y. (1992). *Effects of using calculators on computational ability of non-college bound students, their attitudes toward mathematics and achievements on unit tests in probability and statistics* (Doctoral dissertation). DAI-A, 52/07. UMI No. 9134970

Ling, S. (2004). *Enhancing the learning of conics with technology* (Master's thesis). MAI, 42/05M. UMI No. 1418942

Liu, S. T. (1993). *Effects of teaching calculator use and problem-solving strategies on mathematics performance and attitude of fifth-grade Taiwanese male and female students* (Doctoral dissertation). DAI-A, 54/12. UMI No. 9414962

Lodree, A. (2006). *The effects of animated agents with verbal audio on mathematics comprehension and attitudes towards mathematics and computers* (Doctoral dissertation). DAI-A, 67/09. UMI No. 3235852

Love, T. R. (2004). *Computer-assisted remedial mathematics instruction* (Master's thesis). MAI, 43/03M. UMI No. 1423779.

Lunder, D. A. (1979). *The impact of the calculator on test anxiety for high school consumer mathematics students* (Doctoral dissertation). DAI-A, 39/11. UMI No. 7910673

Maag, M. H. (2002). *The effectiveness of an interactive multimedia learning explanation on baccalaureate nursing students' mathematical achievement and self-efficacy* (Doctoral dissertation). DAI-B, 63/11. UMI No. 3071586

May, P. L. (2005). *Analysis of computer algebra system tutorials using cognitive load theory* (Doctoral dissertation). DAI-A, 66/05. UMI No. 3177549.

Miles, M. M. (1980). *A study of the interrelationship of the hand-held calculator, achievement in mathematical computation and problem-solving, and attitude toward mathematics of eighth grade students* (Doctoral dissertation). DAI-A, 41/03. UMI No. 8018831

Mirick, J. L. (2002). *Benefits of a calculator tutorial in a college algebra classroom* (Doctoral dissertation). DAI-A, 63/11. UMI No. 3017560.

Morgan, P. & Ritter, S. (2002). *An experimental study of the effects of Cognitive Tutor Algebra I on student knowledge and attitude.* Pittsburg, PA: Carnegie Learning. Retrieved from https://www.carnegielearning.com/static/web_docs/morgan_ritter_2002.pdf

Myers, J. L. (1996). *The influence of a take-home computer program on mathematics achievement and attitudes of Title I elementary school children* (Doctoral dissertation). DAI-A, 57/07. UMI No. 9636476

Netusil, A. J., Kockler, L. H. (1974). *CAI: Overcoming attitude barriers* (Technical report). Ames, IA: Iowa State University. Retrieved from https://eric.ed.gov/?id=ED097910

Nwabueze, K. K. (2006). Technology class format versus traditional class format in undergraduate algebra. *Technology, Pedagogy, and Education, 15*, 79-93.

Odom, S. B. (2006). *The effects of self-regulated learning strategies and technology instructional strategies on the math achievement of junior high students* (Doctoral dissertation). DAI-A, 67/05. UMI No. 3218878

O'Dwyer, L. M., Carey, R., & Kleiman, G. (2007). A Study of the Effectiveness of the Louisiana Algebra I Online Course. *Journal of Research on Technology in Education, 39,* 289-306.

Ogbuehi, P. L., & Fraser, B. J. (2007). Learning environment, attitudes and conceptual development associated with innovative strategies in middle-school mathematics. *Learning Environments Research, 10*, 101-114.

Paasonen, J. (1980). *The electronic hand calculator in Finnish comprehensive school mathematics teaching (Research Bulletin No. 53)*. Helsinki, Finland: University of Helsinki, Institute of Education. Retrieved from https://eric.ed.gov/?id=ED201468

Pankow, C. K. (1994). *The effects of college student use of graphics calculators on the learning of algebraic concepts* (Doctoral dissertation). DAI-A, 55/12. UMI No. 9511388

Pilli, O., & Aksu, M. (2013). The effects of computer-assisted instruction on the achievement, attitudes and retention of fourth grade mathematics students in North Cyprus. *Computers & Education, 62,* 62-71.

Plourde, J. (2008). *The effect of inquiry-based, hands-on math instruction utilized in combination with web-based, computer-assisted math instruction on 4th-grade students' outcomes* (Doctoral dissertation). DAI-A 69/09. UMI No. 3324659.

Reagan, L. (2004). *The effectiveness of computer-assisted instruction in developmental mathematics classes* (Doctoral dissertation). DAI-A, 65/10. UMI No. 3151910

Reed, B. (2008). *Effects of virtual manipulatives in algebraic thinking on preservice teacher mathematics courses* (Doctoral dissertation). DAI-A, 69/03. UMI No. 3304569

Riley, A. G. (1992). *Effects of integrating TI Math Explorer Calculators into the grades 3 through 6 mathematics curriculum on achievement and attitude* (Doctoral dissertation). DAI-A, 54/05. UMI No. 9315129

Roberts, D. M. & Glynn, S. M. (1979). Teaching introductory statistics for psychology: Effects of calculators on performance and motivation. *Perceptual and Motor Skills, 48,* 563-569.

Robison, S. A. (1996). *The effects of computer animated instruction in college trigonometry on student achievement, conceptual understanding, and student attitudes* (Doctoral dissertation). DAI-A, 57/08. UMI No. 9700103

Rose, L. L. (2001). *The use of software with low-achieving students: Effects on mathematics attitude and achievement* (Doctoral dissertation). DAI-A, 62/05. UMI No. 3014799

Ross, J. A., Bruce, C. D., & Sibbald, T. M. (2011). Sequencing computer-assisted learning of transformations of trigonometric functions. *Teaching Mathematics & its Applications, 30,* 120-137.

Ross, J. A., Sibbald, T., & Bruce, C. D. (2009). Characteristics of students assigned to technology-based instruction. *Journal of Computer Assisted Learning, 25,* 562-573.

Ryan, W. F. (1999). *The effects of using the TI-92 calculator to enhance junior high students' performance in and attitude toward geometry* (Unpublished technical report). Retrieved from https://eric.ed.gov/?id=ED436414

Santiago-Collazo, D. (1995). *The effects of the use of a Logo computer experience on geometry problem-solving for Hispanic limited English proficient migrant elementary students* (Doctoral dissertation). DAI-A, 56/05. UMI No. 9532017

Saunders, J., & Bell, F. H. (1980). Computer-enhanced algebra resources: Their effects on achievement and attitudes. *International Journal of Mathematical Education in Science and Technology, 11*, 465-473.

Schumacker, R. E., Young, J. I., & Bembry, K. L. (1995). Math attitudes and achievement of Algebra I students: A comparative study of computer-assisted and traditional lecture methods of instruction. *Computers in the Schools, 11,* 27-33.

Seal, J. (2008). *A comparison of academic achievement and retention of community college students in college algebra after completion of traditional or technology-based instruction* (Doctoral dissertation). DAI-A, 69/02. UMI No. 3297775

Shiah, R. (1994). *The effects of computer-assisted instruction on the mathematical problem* *solving of students with learning disabilities* (Doctoral dissertation). DAI-A, 55/08. UMI No. 9501770

Shneyderman, A. (2001). *Evaluation of the cognitive tutor algebra 1 program.* Miami, FL: Miami-Dade County Public Schools. Retrieved from http://oer.dadeschools.net/algebra.pdf

Smith, K. B. (1991). *An integration of the computer algebra system DERIVE into instruction of linear programming* (Doctoral dissertation). DAI-A, 52/10. UMI No. 9200846

Sorensen, C. (2011). *Learning with mobile technologies: The use of out-of class short message system text messaging to support the classroom learning of high school algebra* (Doctoral dissertation). DAI-A, 72/03. UMI No. 3439543

Spence, D. J. (2004). *Engagement with mathematics courseware in traditional and online learning environments: Relationship to motivation, achievement, gender, and gender orientation* (Doctoral dissertation). DAI-A, 65/02. UMI No. 3123365

Spinelli, M. A. (2001). The use of technology in teaching business statistics. *Journal of Education for Business, 77,* 41-44.

Taylor, J. M. (2006). *The effects of a computerized-algebra program on mathematics achievement of college and university freshmen enrolled in a developmental mathematics course* (Doctoral dissertation). DAI-A, 67/12. UMI No. 3246424

Thomas, B. S. (2002). *A computer-assisted instruction approach to supplement the classroom instruction addressing mathematics of finance* (Doctoral dissertation). DAI-A, 64/04. UMI No. 3088034

Tintera, P. J. (2004). *The facilitative role of graphing calculators in learning college algebra: An analysis of adult learner's learning style and self-efficacy in mathematics* (Doctoral dissertation). DAI-A, 65/06. UMI No. 3137270

Voloshin, D. (2009). *An evaluation of a computer-assisted, remedial algebra curriculum on attitudes and performance of ninth grade English learners* (Doctoral dissertation). DAI-A, 70/07. UMI No. 3367762

Webster, A. H. (1990). *The relationship of computer-assisted instruction to mathematics achievement, student cognitive styles, and student and teacher attitudes* (Doctoral dissertation). DAI-A, 51/10. UMI No. 9103410

Weems, G. H. (2002). Comparison of beginning algebra taught onsite versus online. *Journal of Developmental Education, 26,* 10-18.

Wodarz, N. (1994). *The effects of computer usage on elementary students' attitudes, motivation and achievement in mathematics* (Doctoral dissertation). DAI-A, 55/12. UMI No. 9512915

Wohlgehagen, K. S. (1992). *A comparison of the attitude and achievement in mathematics of Algebra I students using computer-based instruction and traditional instructional methods* (Doctoral dissertation). DAI-A, 53/12. UMI No. 9311345

Yang, K. H. (2014). The WebQuest model effects on mathematics curriculum learning in elementary school students. *Computers & Education, 72,* 158-166.

Zunker, L. J. (2008). *Computer-based instruction and mathematics skills of elementary students with learning disabilities* (Doctoral dissertation). DAI-A, 69/10. UMI No. 3332683