The effectiveness of MyMathLab in College Algebra: A meta-analysis

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College algebra is a gatekeeper course for attaining degrees and higher-paying jobs. Computer-assisted instruction (CAI) programs such as MyMathLab (MML) may help close the achievement gap among college algebra students. The purpose of this study was to conduct a meta-analysis to determine the overall effectiveness of MML among college algebra students. The data pooled from a total of ($k = 7$) quasi-experimental primary studies that summarized the mean effect sizes using Hedge's g in a forest plot was based on the random-effects model. The results of this meta-analysis yielded a significant effect ($g = 0.201$, $p = 0.037$, 95% CI [0.012 to 0.390]) favoring MML over traditional instruction among college algebra students with a low amount of heterogeneity in true outcomes detected ($Q = 9.392$, $p = 0.153$, $t^2 = 0.020$, $I^2 = 31.130\%$). This is the first known study to use a meta-analytic approach to determine the overall effectiveness of MML in college algebra. The study's findings, which revealed significant evidence that teaching with MML was more effective than traditional instruction, offered assurance to the uncertainty.

keywords: college algebra; MyMathLab; educational technology; computer-assisted instruction

The effectiveness of MyMathLab in College Algebra: A Meta-analysis

College algebra remains one of the most challenging subjects among first-year college students. About 40 percent of undergraduate college students do not continue education after freshman year (Hanson, 2021). Because college algebra is often the culprit for students dropping out (Chen, 2013), educators are revisiting teaching strategies to align curriculum with adaptive computer-assisted instruction (CAI) programs (Rathmell, 2018). The orthodox styles of teacher-centered education utilizing solely traditional pencil-and-paper are becoming obsolete in today's education. Isupova and Suvorova (2018) asserted that implementing adaptive learning and enhance cognitive thinking is to make use of digital resources in the classroom. Numerous studies have investigated the effectiveness of MyMathLab (MML) in mathematics (Burch & Kuo, 2010; Chekour, 2017; Klein, 2005; Lloyd, 2012; Plummer, 2008). Supplying educators with computer-assisted tools such as MML helps to modernize the curriculum while preparing future generations of young scholars for the expeditious development of economics, industry, and technology (Barakaev et al., 2020). Assessing the effects of MML can broaden understanding of the effectiveness of adaptive CAI programs.

The purpose of this study was to contribute to the knowledge of the overall effectiveness of MML among college algebra students. The study aims to answer the following research question: What is the overall effectiveness of MML among college algebra students? By using a meta-analysis, for which previous studies are collected and codified in order to compare mathematical achievement after administering varying amounts of MML, more accurate generalizations can be posited. This quantitative study focused on collecting similar empirical primary (published and unpublished) studies that determine connections between MML and mathematical achievement among college algebra students.

Within this meta-analysis, the overall effectiveness of MML among college algebra students was determined. In an attempt to address the high failure rates among first-year college students in college algebra, it was important to research teaching models that incorporated MML in college algebra courses. In addition to informing teaching strategies to improve the way students comprehend and perceive mathematics, this research was significant for developing policies and procedures geared toward increasing student success rates in college algebra and contributes to subsequent research in the field of mathematics education.

THEORETICAL FRAMEWORK

Behaviorism, when using Operant Conditioning, is a theory of learning which intends to modify human behavior during instructional tasks using positive and negative reinforcement. B. F. Skinner's behaviorism theory can occur naturally with reinforcement, in which the consequences of a response determine the probability the behavior is repeated (McLeod, 2007). Reward increases the chance a behavior is repeated; punishment decreases the chance a behavior is repeated. Behaviorism has been used as a framework for several studies about CAI programs such as MML. For instance, Lewis and Hieb (2013) reported that having students solve MML problems under simulated test conditions encouraged them to develop effective study habits and made for a more pleasant educational experience. Moosavi (2009) applied behaviorism to compare two instructional methods of CAI in a college freshman algebra class, where he argued a student's external behaviors are guided by instructions directed by CAI programs. In another study that compared traditional instruction to asynchronous computer-assisted instruction among developmental mathematics students, Hogan (2005) asserted that CAI is linked to B. F. Skinner's theory due to its drill-and-practice aspects. In Pandey's study (2021) where the researcher examined the effectiveness of CAI in teaching mathematics, behaviorism was cited as the theory underlying CAI because programmed instruction influenced mathematics education. This study follows the path of the behavioral theories proposed by B. F. Skinner because MML, and other CAI programs, replicate behaviorism on a computer monitor (Kohn, 2012).

LITERATURE REVIEW

There is widespread concern in the United States among school officials that college algebra presents substantial barriers to college students in pursuit of a degree or credential (Chen, 2013). Students discontinuing college algebra, and ultimately higher education, create a cascade effect that has long-term ramifications on the degree attainment and the workforce. Nayak (2017) reported that poor performance in gateway courses such as college algebra not only affects students' self-esteem and academic standing but has lasting consequences beyond college because students are prevented from earning a degree in science or engineering that may yield higher-paying jobs. This dilemma has galvanized administrators and educators to think outside the box and modernize instructional methods by using CAI programs and other technologies in introductory math courses in order to improve success rates (Harrell-Williams et al., 2020).

Computer-Assisted Instruction (CAI)

Computer-Assisted Instruction (CAI) is the use of interactive computer programs that deliver academic content and remediate learning for students (Gulzar, 2022). Arnold (2000) described CAI as an innovative technological teaching tool used to encourage student engagement by embedding sound, pictures, videos, animation, and interactive media to make the information more intriguing and understandable. CAI programs use drill-and-practice, prompt questions, and provide instant feedback with hints, clues, and reinforcement based on the student's answers (Arnold, 2000).

CAI in College Algebra

To accommodate a growing diverse student body attending colleges and universities, virtual learning environments that included CAI programs were introduced as a teaching tool to aid in the mastery of college algebra (Twigg, 2003). Some studies revealed CAI's promising effectiveness in college algebra courses. Hagerty and Smith (2005) reported results that showed college algebra students using the adaptive-learning program ALEKS outperformed traditional students on a comprehensive final exam. In one iteration, Boyce and O'Halloran used ALEKS-generated data to design more peer activities that matched student progress. As a result, a positive change in retention rates at higher mathematics levels was observed. More recently, Melnikova et al. (2020) conducted a study investigating the relationship between final course grades and time spent in the college algebra tutoring lab using ALEKS that resulted in 79% of students using the lab earning a "D" grade or better versus 48% of students who did not.

In another study, Ye and Herron (2012) determined a significant relationship between the number of hours that college algebra students spent in the computer lab and final exam performance. Herron et al. (2012) compared computer algebra systems to traditional college algebra instruction. Comparing the final grades of enrolled students over three consecutive semesters, it was determined success rates were higher among computer-assisted college algebra sections. A study by Johnson (2019) provided evidence that college algebra students' interaction with dynamic computer activities significantly improved their attitudes and performance in math.

MyMathLab (MML)

MML is advertised on its webpage as a top-notch educational program designed with a user-friendly format to assist students and teachers in the learning process (Pearson, 2023a). After finishing a study that Pearson researchers conducted to investigate how the interactive online learning system affects student learning outcomes, a plethora of supporting evidence was claimed (Pearson, 2023b). An academic research study from Pensacola State College showed students' module PostTest scores increased on average by about 40 percent from their module PreTest scores, demonstrating that students were five times more likely to succeed if they were given more homework, quiz, and exam attempts (Pearson, 2023c). This suggests a very strong correlation between the repetition of practice problems and ability to master quizzes and exams.

MML in College Algebra

Several studies confirmed the positive findings declared by Pearson. For example, Plummer (2008) studied mathematical achievement in five skill areas by comparing final exam scores of Marion Technical college algebra students using MML to students without MML. Findings revealed that MML mean scores were higher in all five skills areas than traditional mean scores. Leveille (2008) evaluated college algebra students' pass rates in both traditional and MML courses to infer which instructional approach was most effective. Based on the findings, Leveille determined that in both Fall 2006 and Spring 2007 semesters, pass rates were higher among college algebra students using a web-based homework delivery system consisting of MML. There was a statistically significant difference in pass rates among college algebra students using the Rockswold textbook supplemented with MML homework (Leveille, 2008).

During the Fall 2010 and Fall 2011 semesters, Lazari and Reid (2013) compared large college algebra sections using MML that consisted of 150 and 175 students, respectively, to a traditional college algebra section consisting of 35 students. After comparing both groups, there was a statistical difference between the means of the final exams, where the large college algebra section outperformed the traditional college algebra section. Lazari and Reid concluded, if proper care and planning with the appropriate instructional delivery system are taken, larger sections of college algebra can be beneficial and cost-effective. Krupa et al. (2013) compared final exam scores between college algebra students in traditional lecture-based and computer-based sections. Results indicated final exam scores in the computer-based section were significantly higher than in the traditional section. Similarly, Graham and Lazari (2018) collected data in the Fall semester 2016 and Spring semester 2017 to determine if there is a difference in departmental final exam scores between the online section using MML and the traditional section. Online students who used MML had statistically significantly higher departmental scores.

Snyder (2006) conducted a mixed-methods study exploring the role of teachers and students in a computer-based college algebra class using MML. Addressing the utility that a computer-based college algebra course has, Snyder reported students viewed their role as having more responsibility and self-direction. Simultaneously, the teacher pursued the role of facilitating rather than directive behaviors. Warren (2018) investigated how online students interpret and understand college algebra in a virtual classroom. Based on the narratives of four students in an asynchronous college algebra course, results showed technology helped deliver course content to students, allowing them to think about college algebra in a different way. Khasawneh et al. (2023) compared the effects of inquiry-based learning with traditional lectures among college algebra students where both groups were supplemented with MML. Measuring mathematical achievement scores with a pre-and post-test model, they determined that the inquiry-based group's mean achievement score was significantly higher than the traditional lecture group.

It is clear from many of the primary studies identified that MML is a powerful learning tool for both students and instructors to use in college algebra courses. However, in many cases, the literature available does not provide significant evidence of its effectiveness compared to traditional methods of instruction. For instance, at Texas Tech University, Klein (2005) researched how the use of computer-assisted instruction, using MML, affected the knowledge gained by college algebra students. Comparing one section of college algebra that used traditional instruction augmented with MML with another section of college algebra that used only traditional instruction in the Spring semester of 2005, the change in test scores was not statistically significant.

Additional studies failed to provide evidence that MML is effective in college algebra. For example, Harris (2008) conducted a study that compared the effectiveness of traditional and non-traditional homework assessment schemes over one year. The traditional scheme had college algebra students work problems from the textbook and the non-traditional scheme had students use an online assessment component of MML, Math XL. The study implied no statistical difference in persistence or success by using Math XL versus a traditional textbook among college algebra students. Another yearlong study by Burch and Kuo (2010) at Indiana University of Pennsylvania also compared final exam scores between the pencil-and-paper group and MML group in multiple college algebra sections. Despite students in MML sections scoring higher on the final exam, there was insufficient evidence to infer that the mean score of the final exam from the MML group was higher than the mean score of the final exam from the pencil-and-paper group. Comparing the final exam scores of a traditional section with an MML section of Fayetteville University college algebra students, Kodippili and Senaratne (2008) concluded that there is not enough evidence that students in the group with computer-generated homework outperformed the students using traditional paper-based homework.

Some studies indicated potential for MML, but not enough evidence to make any definitive conclusions regarding its effectiveness. For example, a study conducted in Fall 2012 revealed college algebra students using MML in the online and hybrid groups did only moderately better than students in the traditional group that did not use MML (Lloyd, 2012).

The literature involving the implementation of MML in college algebra was divided. Because there was conflicting evidence in the literature on whether or not MML is effective in college algebra, conducting a meta-analysis might provide closure to the debate.

MATERIALS AND METHODS

This meta-analysis followed the seven-step model delineated by Cooper (2017) for the analytic process:

1. Step 1: Formulating the problem. During problem formulation, Cooper (2017) suggested the meta-analyst should decide on the concepts, interventions, and

outcomes relevant (or irrelevant) to the study. A well-defined research question and an associated hypothesis that properly aligns with the research topic were created.

2. Step 2: Searching the literature. This step requires identifying sources that can be used to find relevant information on the research topic. Additionally, it is essential to find studies that permit the meta-analyst to make accurate generalizations about the population of interest (Cooper, 2017). By utilizing databases, search engines, scanning articles and books, and contacting content experts, an exhaustive literature search concerning the effectiveness of MML in college algebra was conducted.
3. Step 3: Gathering information from studies. A protocol should be developed for gathering necessary information from relevant studies. Known as the coding phase, the abstracts of primary studies were collected and screened while relevant information was extracted that included the study's setting, participants, methodology, outcome measures, and statistical results (Cooper, 2017).
4. Step 4: Evaluating the quality of studies. In this step, a determination needs to be made on what studies to include and exclude from the synthesis (Cooper, 2017). The inclusion and exclusion criteria were based on the Population, Intervention, Comparison, and Outcomes (PICO) model, study design, and the publication year (Tawfik et al., 2019). Studies were excluded in this meta-analysis by reading the abstracts to determine whether the studies are duplicated, unrelated, or irrelevant.
5. Step 5: Analyzing and integrating the outcomes of studies. Once the data has been extracted, statistical procedures are used to analyze data and calculate effect sizes (Cooper, 2017). Because a small number of primary studies fulfilled the inclusion and exclusion criteria, Hedge's g was used to calculate effect sizes because it is better for correcting biases when the sample size is small (Borenstein et al., 2021; Cooper & Hedges, 2009; Glen, 2016).
6. Step 6: Interpreting the evidence. The meta-analyst examined the data to determine the magnitude and direction of the effect sizes as well as draw conclusions with respect to the generality or specificity of the findings (Cooper, 2017).
7. Step 7: Presenting the results. The results were presented and discussed in a logical and lucid manner to highlight the key findings of the meta-analysis (Cooper, 2017).

SAMPLING CRITERIA AND PROCEDURES

Published journal articles, theses and dissertations, and conference papers were the main sources searched. The following search phrases were utilized: *MyMathLab AND college algebra; Math XL AND college algebra; MyLab Math AND college algebra; computer-assisted instruction AND college algebra*. Additionally, the term "computer-assisted instruction" was replaced with the following sub-terms used with the conjunction "AND" with college algebra: computer-aided instruction, computer-augmented instruction; computer-based education (CBE); computer-based learning (CBL); computer-based teaching (CBT); computer-enriched instruction (CEI); artificial intelligence (AI); intelligent learning environments (ILE); intelligent tutoring systems (ITS), personalized learning (PL); immersion method (IM). In addition to *Google Scholar* and manually searching relevant Internet sites, the major databases, search platforms, and search engines through Texas A&M University - Kingsville Jernigan Library were included: *ProQuest Dissertations & Theses Global (PQDT), EBSCO Information Services, Educational*

Resources Information Center (ERIC), and *Academic Search Complete.* References listed in the primary studies gathered were used as another source to further expand the search results.

The sampling frame included the universe of primary studies that address the overall effectiveness of MML among college algebra students. Sample size was determined depending on how many primary research studies have been selected for this meta-analysis. The following inclusion and exclusion criteria were used:

1. Only studies between 2005 and 2023 which consisted of quasi-experimental and comparative designs were included. Other studies with different research designs were initially collected but ultimately excluded from the data analysis to prevent substantial dissimilarity between studies.
2. The three main sources for this meta-analysis included: published journal articles, dissertations, and conference papers.
3. Only studies with varying degrees of MML treatment were included. Among the studies included three main roles of MML were identified: students were taught with no MML (traditional), student instruction was augmented with MML (supplemental), or students were completely self-taught with MML (immersed).
4. Only studies that measured the effectiveness of MML with college algebra achievement scores were included. College algebra achievement scores resulted from formal assessments such as tests and final exams.
5. Only studies of college algebra students enrolled in a university or community college were included in the population of interest.
6. The studies included compared the effectiveness of MML against that of traditional instruction using a wide range of research designs and time periods.
7. Only studies written in English and conducted in the United States were included.

Validation

The PICO (Population-Intervention-Comparison-Outcome) model was helpful in constructing a framework for the research question and determining essential components needed in the study. The random-effects model was selected a priori as, unlike a fixed-effect model that assumes a fixed population effect size, this model assumes more than one true effect size (Fang et al., 2019). Jamovi (Version 2.4) software was used to analyze data. The abstracts of articles were used to exclude irrelevant studies. Reviewing and coding the primary data were performed by the primary researcher. Hedge's g was chosen over Cohen's d and Glass's Δ because it is superior for correcting biases when the sample size is small (Borenstein et al., 2021; Cooper & Hedges, 2009; Glen, 2016). Hedges's g is defined by (Rosenthal et al., 1994)

$$g = \frac{M_E - M_C}{S_{pooled}}$$

where M_E and M_C are the means of the experimental group and control group, respectively, and with the pooled sample standard deviation (Hedges & Olkin, 1985)

$$S_{pooled} = \sqrt{\frac{(n_E - 1){S_E}^2 + (n_C - 1){S_C}^2}{n_E + n_C - 2}}$$

where n_E and n_C are the sample sizes of the experimental and control groups, and S_E and S_C are the standard deviations of the experimental and control groups, respectively (Hsu, 2003). All effect sizes from each study were converted to Hedge's g using Jamovi software (Version 2.4). A forest plot was used to provide context about the mean effect size (the center of the diamond) and its confidence interval (the width of the diamond) (Borenstein et al., 2021).

DATA ANALYSIS

Jamovi software (Version 2.4) was used to analyze data. The abstracts of the articles were used for data screening and cleaning to exclude irrelevant studies. Reviewing and coding the primary data was performed by the researcher. To compute the effect sizes for each study, the inferential and descriptive statistics specify the mean μ, standard deviation σ, and variance σ^2.

Due to the likelihood of encountering smaller samples ($n < 20$) in selected studies, Hedge's g is chosen over Cohen's d and Glass's Δ because it is superior for correcting biases when the sample size is small (Borenstein et al., 2021; Cooper & Hedges, 2009; Glen, 2016). All effect sizes from each study are converted to Hedge's g using Jamovi software (Version 2.4) and a forest plot was used to provide context about the mean effect size (the center of the diamond) and its confidence interval (the width of the diamond) (Borenstein et al., 2021).

There were 2,575 potential studies post search. Abstracts of these studies were screened for keywords to determine whether the studies were pertinent to the research topic. Initially, 34 studies were seriously considered for the meta-analysis. Of these studies, 26 were ultimately disqualified for not meeting the inclusion and exclusion criteria. The remaining eight studies met the inclusion and exclusion criteria; however, one research study was excluded from the meta-analysis because essential data was missing. There was an attempt to contact the authors of the research study to obtain the necessary information, but no response was received. Figure 1 depicts a Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram of the studies included in the meta-analysis.

The meta-analysis included a total of seven primary studies. Five of the studies ($k = 5$, 71%) were published, consisting of three journal articles, one conference paper, and one dissertation. Two ($k = 2$, 29%) were unpublished, consisting of two theses. Dates of the seven primary studies ranged between 2005 and 2018. A total of ($N = 1{,}503$) participants in this review, with a total of ($N_E = 286$) participants in the experimental groups and a total of ($N_C = 1{,}217$) participants in the control groups. Table 1 details information on study sample size.

The study by Graham and Lazari (2018) revealed a noticeable discrepancy in sample size between the experimental and control groups. Specifically, the experimental group consisted of 34 participants who received online instruction utilizing MML whereas the control group had 921 persons who were taught in a traditional instruction format. For this reason, the study by Graham and Lazari (2018) stands out as an outlier. Except Graham and Lazari (2018) which compared an online class using MML to face-to-face traditional instruction, all studies used some kind of hybridized intervention that consisted of traditional instruction supplemented with MML. A sensitivity analysis will be presented that excludes the study by Graham and Lazari (2018) to determine the robustness of the meta-analytic findings.

META-ANALYSIS RESULTS

A total of ($k = 7$) quasi-experimental primary studies were included in this analysis and results are presented in Table 2. Based on a random-effects model, the estimated average standardized mean difference (SMD) was $g = 0.201$ with a 95% confidence interval given by 0.012 to 0.390. The mean effect size in the universe of comparable studies could fall anywhere in the confidence interval (Borenstein et al., 2021). As a result, the average outcome deviated from zero ($z = 2.090$, $p = 0.037$), indicating a statistically significant positive effect at alpha < .05 favoring MML over traditional instruction.

The SMD is the measure of effect sizes that represent the magnitude of difference in college algebra mathematical achievement between the experimental and control groups (Borenstein et al., 2021). This implies that positive effect sizes show a difference that favors MML, whereas negative effect sizes indicate a difference that favors traditional instruction. The standard error was estimated to be 0.097, which specifies the uncertainty of the overall mean effect (Deeks et al., 2019). The z-value tests the null hypothesis that the mean effect size is zero. The z-value was 2.090 with $p = 0.037$. Using a criterion alpha of 0.050, the null hypothesis was rejected, and therefore, in the universe of populations comparable to those in the analysis, the mean effect size was not precisely zero.

As shown in the forest plot in Figure 2 using Jamovi software (Version 2.4), the SMD expressed as Hedge's $\boldsymbol{g}$ observed among the studies varied from -0.182 to 0.524, such that most estimates were positive ($\boldsymbol{k} = 5$, 71%). The true outcome had a 95% prediction interval given by -0.135 to 0.537. Although the average outcome was estimated to be positive, in some studies the true outcome was actually negative. An examination of the forest plot showed primary study effect sizes varied from -0.182 to 0.524. Among the five studies ($\boldsymbol{k} = 5$) with positive effect sizes, four studies ($\boldsymbol{k} = 4$, 57%) had a small effect, and one study (Graham & Lazari, 2018) had a medium effect. Two studies ($\boldsymbol{k} = 2$, 29%) revealed small negative effect sizes.

Assessing Heterogeneity

As shown in Table 3, Cochran's Q-test which revealed a low amount of heterogeneity identified in true outcomes was not statistically significant ($Q = 9.392$, $p = 0.153$, $t^2 = 0.020$, $I^2 = 31.130\%$). Using a criterion alpha of 0.05, the null hypothesis that the true effect size is the same in all these studies was retained. However, given the limited number of studies and sample sizes, Borenstein et al. (2021) cautioned that the Q-statistic should be regarded with caution.

The H^2 statistic, obtained from Cochran's Q, measures the ratio of the observed variation and the expected variance caused by sampling error (Lortie, 2022). Because when H^2 is equal to 1 indicates perfect homogeneity among studies included (Pathak et al., 2017), the H^2 statistic of 1.452 suggests moderately low heterogeneity among studies. The I^2 statistic of 31.130% revealed that roughly 31.130% of the variance in observed effects may be attributed to differences in true effects rather than to sampling error (Borenstein et al., 2021). In accordance with the I^2 statistic benchmarks defined by Higgins et al. (2003), and in line with the results from the Q-test, the proportion of true heterogeneity was moderately low ($I^2 = 31.130\%$). However, caution is warranted as I^2 may be biased in meta-analyses that contain a small number of studies (Borenstein et al., 2021). Tau squared and tau, denoted as t^2 and t, respectively, reflect the true amount of heterogeneity across studies and are used to compute the prediction interval (Deeks et al., 2019). Based on the variance ($t^2 = 0.0201$) and standard deviation ($t = 0.142$) of true effect sizes, the 95% prediction interval given by -0.135 to 0.537, represents an estimate where the true outcome is expected. The prediction interval reports how the true effect sizes vary across studies using an identical scale as the effect size itself (Borenstein et al., 2021).

Publication Bias

A funnel plot was used to determine publication bias. A visual inspection of plot revealed no obvious asymmetry around overall effect size indicating no evidence of publication bias. While the visual of the funnel plot may be compelling, statistical approaches of Begg and Mazumdar rank correlation test and Egger's regression test offer more precision to assess for publication bias. There was no evidence of publication bias as rank correlation and regression tests indicated no funnel plot asymmetry ($p = 0.562$, $p = 0.321$), respectively (see Table 4).

Sensitivity Analysis Results

A sensitivity analysis was used to determine possible outliers among studies (Botella & Sánchez-Meca, 2015; Littell et al., 2008) and test the robustness of the meta-analytic findings. The study conducted by Graham and Lazari (2018) posed a risk of bias due to several reasons. First, the sample size utilized in the study was significantly larger in comparison to other studies. Additionally, this study was the only study that yielded a statistically significant positive medium effect ($g = 0.520$). Furthermore, this study stands out as the only study in which an intervention involving an MML-based online class was implemented. The results from the sensitivity analysis, which excluded the study (Graham & Lazari, 2018), indicated a total of ($k = 6$) quasi-experimental primary studies. These results are presented in Table 5.

The SMD observed among the studies varied from -0.182 to 0.356, such that most estimates were positive (67%). Based on a random-effects model, the estimated average SMD was $g = 0.132$ with a 95% confidence interval given by -0.048 to 0.311 depicted in a forest plot, as shown in Figure 3. Therefore, the average outcome did not deviate from zero ($z = 1.435$, $p = 0.151$) suggesting MML supplemented with traditional instruction was more effective than traditional instruction alone but not significantly so at alpha < .05. Although the average outcome was estimated to be positive, in some studies the true outcome may actually be negative.

As shown in Table 6, the Q-test which revealed a low amount of heterogeneity identified in true outcomes was not statistically significant ($Q = 5.415$, $p = 0.367$, $t^2 = 0.003$, $I^2 = 6.388\%$). The true outcome had a 95% prediction interval given by -0.080 to 0.344. Because the study by Graham and Lazari (2018) was considered heterogeneous as the only study with a significant effect, excluding this study substantially reduced heterogeneity. Therefore, among the six studies included, a low amount of heterogeneity ($I^2 = 6.388\%$) was detected. A funnel plot was used to determine publication bias. There was no evidence of publication bias detected because the rank correlation and regression tests, as shown in Table 7, indicated no funnel plot asymmetry ($p = 0.719$, $p = 0.767$) respectively.

DISCUSSION

A total of ($k = 7$) quasi-experimental primary studies were included. The SMD expressed as Hedge's g observed among the studies varied from -0.182 to 0.524, such that most estimates were positive (71%). Based on a random-effects model, the estimated average SMD was ($g = 0.201$, 95% CI [0.012 to 0.390]), indicating a statistically significant small positive effect at alpha < .05 favoring MML over traditional instruction. Findings suggest that MML supplemented with traditional instruction was more effective than traditional instruction alone for all the primary studies included in the meta-analysis except one study which (Graham & Lazari, 2018) investigated the effectiveness of MML in combination with traditional instruction.

Although the meta-analytic findings indicated a statistically significant but small positive effect in favor of MML, many of the studies included in the primary analysis did not provide significant evidence likely due to sample size (Harris, 2008; Klein, 2005; Kodippili & Senaratne, 2008; Lloyd, 2012; Mathai & Olsen, 2013; Seal, 2008). However, the large study by Graham and Lazari (2018) did provide a statistically significant positive medium effect ($g = 0.52$, 95% CI [0.18, 0.87]) that favored an online class immersed in MML over traditional instruction.

The present study's findings are consistent with previous meta-analyses about CAI (Akın, 2022; Bangert-Drowns et al., 1985; Burns & Bozeman, 1981; Chadwick, 1997; Christmann et al., 1997; Fletcher, 1990; Hartley, 1977; Hillmayr et al., 2020; Kuchler, 1998; Kulik et al., 1985; Kulik & Fletcher, 2016; Kulik & Kulik, 1991; Liao, 2007; Niemiec & Walberg, 1985; Schmidt et al., 1985; Sosa et al., 2011; Ulum, 2022; Willett et al., 1983). These authors compared CAI with traditional instruction and found statistically significant evidence in favor of CAI. Because MML is a type of CAI program used frequently in educational settings, the meta-analytic findings corroborate the claims that adaptive multimedia features may capture students' attention and create a learning environment conducive to positive outcomes.

Previous research on the effectiveness of MML in college algebra was divided. While some studies (Graham & Lazari, 2018; Khasawneh et al., 2023; Krupa et al., 2013; Leveille, 2008; Plummer, 2008) presented statistically significant evidence supporting the effectiveness of MML, other studies (Burch & Kuo, 2010; Harris, 2008; Klein, 2005; Kodippili & Senaratne, 2008; Lloyd, 2012; Mathai & Olsen, 2013; Seal, 2008) did not provide significant evidence in favor of MML. Although this meta-analysis validates the results of primary studies with statistically significant findings, it reinforces the divergent results found in the literature based on producing a significant but small effect. However, this study extends the body of knowledge by informing teaching strategies to improve mathematical achievement among college algebra students, which is vital for reducing the high failure and low retention rates in college algebra.

The meta-analytic findings build on the existing evidence that CAI programs, when supplemented with traditional instruction, may provide a more advantageous learning environment for students. While previous meta-analyses have focused on CAI program efficacy, this study's findings, which revealed significant evidence that teaching with MML was more effective than traditional instruction, may have important implications in the field of mathematics education by offering some assurance to the uncertainty. However, only a small positive overall effect ($g = 0.201$) favoring MML over traditional instruction was detected, implying the actual difference between the overall group means was present but trivial. Additionally, a sensitivity analysis later revealed differing results from the primary analysis, indicating the meta-analytic findings need to be interpreted with caution (Aromataris & Munn, 2020). Nevertheless, these meta-analytic findings suggest that educational leaders and policymakers can make better informed decisions to address the high failure and low retention rates in college algebra. Furthermore, those evaluating CAI for learner use can utilize the findings with the aim of improving student learning and facilitation using technological tools.

In an attempt to curb the high failure rates among college algebra students, the meta-analytic findings suggest that future practitioners may apply teaching models that incorporate MML in college algebra courses to enhance mathematical proficiency. These findings have considerable significance in reshaping the cultural perspectives of how students and educators view the pedagogical approaches to college algebra and may be extended to encompass other mathematical disciplines. In order to better aid college algebra students, educational leaders and practitioners may want to include MML as part of the subject's core curriculum. Supplying educators with CAI programs such as MML could help modernize the curriculum and prevent future generations of college algebra students from repeating the same patterns of struggle and missed opportunities.

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Table 1
Sample Size Table

Study	Sample size of experimental group	Sample size of control group	Total sample size of study
	n_E	n_C	n
Graham & Lazari (2018)	34	921	955
Harris (2008)	37	33	70
Klein (2005)	30	29	59
Kodippili & Senaratne (2008)	34	38	72
Lloyd (2012)	53	121	174
Mathai & Olsen (2013)	48	29	77
Seal (2008)	50	46	96
	$N_E = 286$	$N_C = 1217$	$N = 1503$

Table 2
Random-Effects Model Statistics of Mean Differences (k = 7)

	Estimate	*SE*	*z*	*p*	CI Lower Bound	CI Upper Bound
Intercept	0.201	0.0965	2.09	0.037	0.012	0.390

Note: t^2 Estimator: Hedges

Table 3
Heterogeneity Statistics

t	t^2	I^2	H^2	R^2	*df*	*Q*	*p*
0.142	0.0201 (*SE* = 0.0402)	31.13%	1.452		6.000	9.392	0.153

Table 4
Publication Bias Assessment

Test Name	Value	*p*
Fail-Safe *N*	7.000	
Begg and Mazumdar Rank Correlation	−0.238	0.562
Egger's Regression	−0.992	0.321
Trim and Fill Number of Studies	0.000	

Note: Fail-safe *N* Calculation Using the Orwin Approach

Table 5
Sensitivity Analysis Random-Effects Model Statistics of Mean Differences (k = 6)

	Estimate	*SE*	*z*	*p*	CI Lower Bound	CI Upper Bound
Intercept	0.132	0.0917	1.44	0.151	−0.048	0.311

Note: t^2 Estimator: Hedges

Table 6
Sensitivity Analysis Heterogeneity Statistics

t	t^2	I^2	H^2	R^2	df	Q	p
0.057	0.0033 (SE = 0.0324)	6.39%	1.068		5.000	5.415	0.367

Table 7
Sensitivity Analysis Publication Bias Assessment

Test Name	Value	p
Fail-Safe *N*	6.000	
Begg and Mazumdar Rank Correlation	−0.200	0.719
Egger's Regression	−0.297	0.767
Trim and Fill Number of Studies	0.000	

Note: Fail-safe *N* Calculation Using the Orwin Approach

Figure 1
PRISMA Flow Diagram

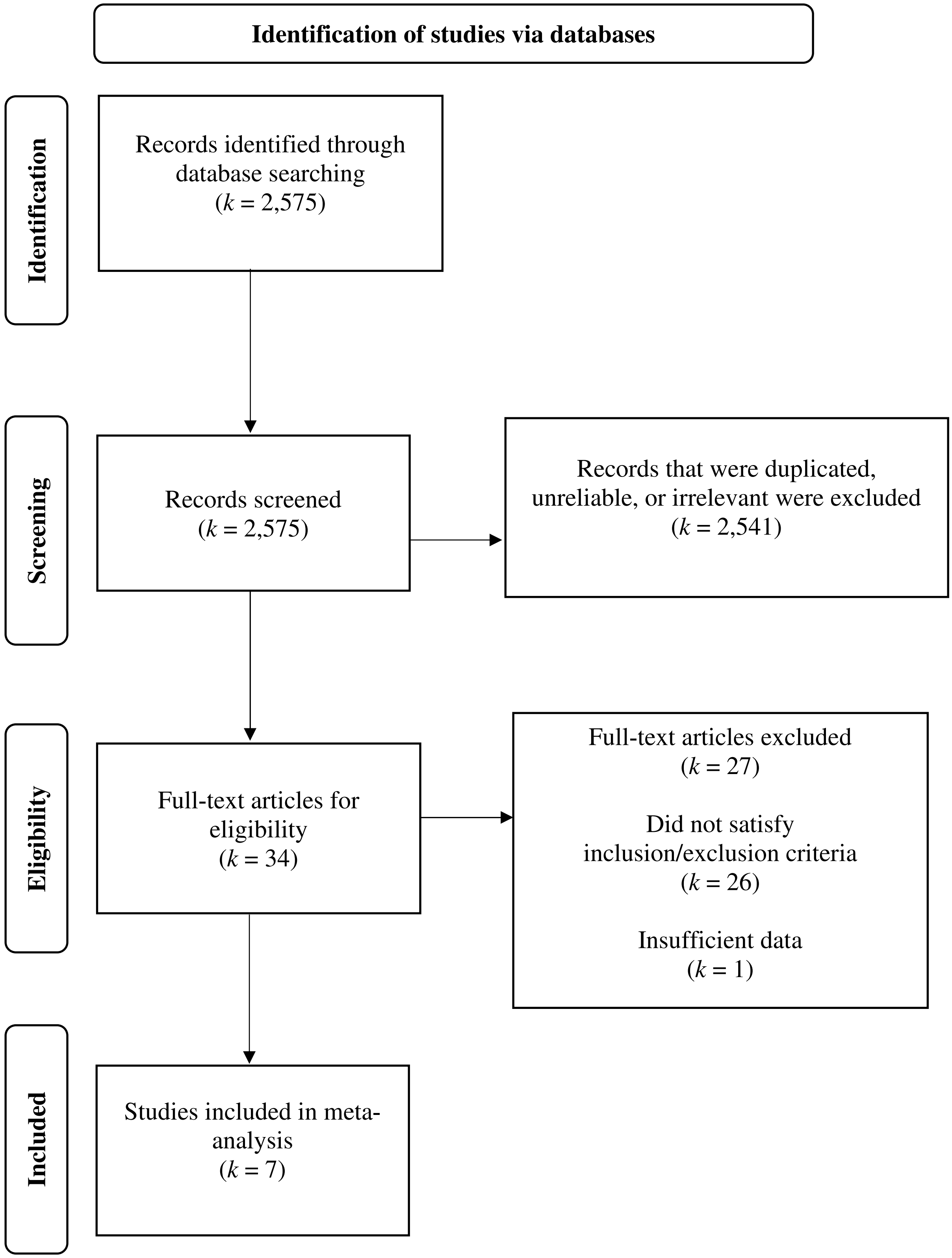

Figure 2

Forest Plot Comparing MML and Traditional Instruction

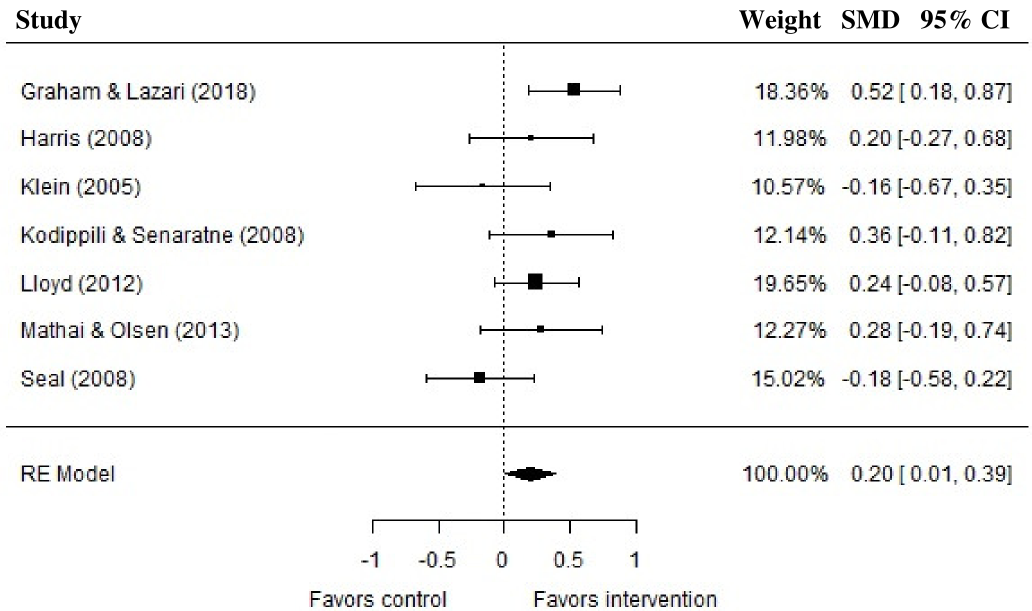

Figure 3

Sensitivity Analysis Forest Plot Comparing MML and Traditional Instruction