A Meta-analysis of the Impact of COVID-19 on Student Achievement

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Abstract

Despite increasing evidence calculating the extent of COVID learning loss, few researchers have attempted to collect and examine the evidence through meta-analysis. To fill this gap, our meta-analysis seeks to explore the existing research regarding the effects of COVID on learning in reading and mathematics. Our findings illustrate that the learning loss was real and significant compared to previous school years. Applying our rigorous inclusion criteria informed by best evidence synthesis methodology, we identified 30 eligible studies. On average, meta-regression results showed that students lost 0.21 ($p = 0.006$) standard deviations of learning during the pandemic school closures. Moderator analysis further showed none of the group comparisons are statistically significant. Marginal means revealed that students lost more in reading compared to math, younger students lost more compared to older students, and students in the U.S. were more negatively affected than students from other countries.

Keywords: COVID-19, academic achievement, learning disruptions, meta-analysis, reading, mathematics

1. Introduction

Starting in March 2020, the education systems of the world were thrown into chaos. Since then, the coronavirus disease 2019 (COVID-19) pandemic has dramatically affected our school systems and the lives and learning of educators and students worldwide in a variety of negative and concerning ways. News organizations, as well as education researchers and practitioners quickly highlighted these issues in real time, as schools across the United States and the world closed as the virus rapidly spread, necessitating the shift to remote learning delivery.

The transition to remote learning, while cutting down on potential infections and spread of the virus, was not seamless in many places. School closures and shifts between remote and hybrid learning models taxed educators and students alike (Pondiscio, 2021; Singer, 2020), while inequitable access to and engagement in learning impeded student opportunities for both academic and social emotional learning (Hough, 2021). These pandemic-caused educational disruptions have been connected to increased student absences (Southall et al., 2021), as well as labor shortages and lower retention rates for teachers (Carver-Thomas et al., 2021), school staff, school bus drivers (McNichol & Leachman, 2020), and school nurses (Buttner, 2021; Cohn, 2021). Teachers, staff, and students have all reported increased levels of trauma and stress as a result of the COVID-19 pandemic (Sparks, 2020; Liang et al., 2020; Etchells et al., 2021). This trend was likely enhanced by the loss or reduction of access to a myriad of non-academic services that schools provide (European Commission et al., 2020; Pier et al., 2021). These services include free and reduced-price meals for students, vision care, asthma and chronic illness support, library resources, study rooms and equipment, vaccinations, counseling, and tutoring, among others. Lacking access to these support services could have immediate and long-lasting consequences on student well-being and ability to engage in learning.

The impact of these changes is most concerning due to concerns over inequitable impacts of education and education services disruption on minority or community of color, low-socio-sconomic-status (low-SES), and at-risk populations of students. In addition to being more reliant on school services (Meeter, 2021) or experiencing previous academic struggles, individuals from these groups have also been found to have been more strongly impacted by the pandemic spread, feeling increased stress levels (Fortuna et al., 2020), disease spread, and social vulnerability (Kim & Bostwick, 2020). Students from lower-SES background families were reported to struggle more with access to online classrooms (Basch et al., 2021) and inappropriate home conditions for remote learning (Pier et al., 2021), and reported less opportunities to interact directly or in live settings with teachers compared to students in higher income areas or backgrounds (Herold, 2020). Distance learning was also identified as being more challenging for younger students (Cottingham, 2020), English language learners (Umansky, 2020), and students with learning disabilities (Mitchell, 2020).

As these changes and difficulties arose, policy makers, practitioners, and researchers issued notices warning of potential harm to student learning progress. The predicted learning losses were soon referred to by a variety of similar terms, including "COVID learning loss" (Kuhfeld et al., 2020), "COVID learning lag (Pier, 2021)," "COVID slide (Bielinski et al., 2020)," "COVID-19 slump (Golinkoff et al., 2020)," "learning disruptions (Ali et al., 2020)" and "unfinished learning (Davidson & Woodward, 2021)," referring to shortcomings in student learning or achievement due to the pandemic.

1.2. Understanding COVID Learning Loss

During the early months of the pandemic, a number of researchers sought to develop models based on existing research about learning loss to predict the potential impact of the pandemic school closures on students (Bielinski et al., 2020; Kaffenberger, 2021; Kuhfeld & Tarasawa, 2020; Kuhfeld et al., 2020), using existing research in summer learning loss, school closures, and absenteeism as a model for potential losses. Estimates were serious, with some estimating about a year of learning loss (Kuhfeld et al., 2020) but usually limited predictions that students might be out of school for a few months at a time, and could not have foreseen the scope and duration of disruptions to education that COVID ultimately caused. Researchers did point to potential differential effects of the pandemic on students already struggling academically or from underrepresented backgrounds. These structural inequitites are not new, but reflect a long-lasting and ingrained opportunity gap (Darling-Hammond et al., 2014; Johnson-Ahorlu, 2012).

As the pandemic spread and school closures continued, concrete data on student outcomes, primarily comparing Fall 2019 and Fall 2020 learning outcomes, were added to the literature, followed by studies comparing Fall 2019 and Spring or Fall 2021 learning outcomes. These reports and studies ranged from state-level assessments to national-level surveys of loss using widely-used standardized assessments such as the Amplify suite of tests. Systematic reviews of the research on COVID learning loss have sought to collate and summarize the findings of these studies, indicating overall learning losses due to school closures both in the United States and abroad, as well as indications that losses may be higher in some demographic groups such as younger students or those from low socioeconomic backgrounds (Donnelly & Patrinos, 2021; Hammerstein et al., 2021; Moscoviz and Evans, 2022; Patrinos et al., 2022; Zierer, 2021). While those studies that sought to project potential negative effects may have been useful in raising awareness of the challenges the pandemic may have caused our education systems, these projections are not as practically useful as measures of actual learning loss, collected through assessments that took place during the pandemic. The systematic reviews provide a useful source for summarizing the results of research measuring actual learning gains or losses, but remain limited due to their lack of deeper meta-analytic analyses. Following a meta-analytic framework enables us to expand on the anslysis provided in a systematic review by allowing us to combine data from multiple primary studies to determine a single impact factor (Glass, 1976; Gopalakrishnan & Ganeshkumar, 2013). This process is more efficient, allows for greater generalizability, improves precision, and data quantification (Gopalakrishnan & Ganeshkumar, 2013).

Some have questioned the focus on learning loss as an unnecessary critique of teachers' superlative efforts to adapt to difficult teaching contexts, or as a mathematical construct propagated by testing enthusiasts (Ewing, 2020a; Ewing, 2020b). However, this declaration minimizes the benefits or uses of these assessments. Properly used assessments of reading and mathematics are not intended as a punishment or weapon against students and teachers, but as a means of identifying areas of need and informing efforts to effectively support remedial learning. This study does not advocate for widespread implementation of standardized assessments, as some (Zhao, 2021) have warned against, or minimizing the focus on addressing students' and teachers' social and emotional needs, but to provide an overview of current research and highlight what these findings can tell researchers and policymakers about the impact thus far of the pandemic on student learning, so that effective, evidence-based interventions may continue to be implemented to address students' needs as the nation and world seek to support school systems and families to adjust to the new normal that the pandemic caused.

1.3. Purpose of the Study

This study attempts to fill a gap in the existing research by compiling the results from individual studies of COVID learning loss in a systematic manner and drawing out trends about the impact of COVID-19 on K-12 student learning in the United States and similar countries. This systematic review and meta-analysis of the COVID learning loss literature seeks to add a deeper understanding of the precise effect COVID has had on learning across subgroups, identifying student learning loss by subject, grade, and nation. The results of the review are intended to provide guidance for policy and practice to address COVID learning loss, or COVID slide, as school districts continue school reopening and COVID recovery initiatives. These findings are intended to provide meaningful and practical information for school districts and policymakers to develop appropriate learning loss remediation policies and programs to address those students most in need of support as schools work to recover from the pandemic.

2. Methodology

To develop an understanding of trends in COVID learning loss, we conducted a meta-analysis on the existing studies measuring COVID learning loss based on measurements of student learning which took place during the pandemic. While there are many studies predicting COVID slide prior to the existence of academic data concerning learning during the course of the pandemic, these studies were excluded. Our meta-analysis instead consisted of quantitative research based on comparing student achievement data prior to and during the pandemic.

2.1. Research Questions and Hypotheses

Our analysis is based on the following research questions:

1. To what extent does COVID-related school closure affect students' learning?

We hypothesize, based on the existing literature highlighting the disruptions to student education and non-academic services (Hammerstein et al., 2021), that COVID-related school closures will seriously and significantly negatively impact student learning.

2. How does this impact differ by students' grade levels, nationality, and subject?

Based on literature and projections related to student learning loss over summer (Shinwell & Defeyter, 2017), disruptions due to emergencies (Kaffenberger, 2021), and extended absences (Kuhfeld et al., 2020), among others, we hypothesize that the COVID pandemic will have a more serious impact for younger students and students in the United

States. Younger students are typically less independent and require more consistent support from teachers and adults, suggesting that disruptions to their access to instruction could have a more detrimental effect. The United States experienced one of the longer school closures, with schools closed in much of the country for the equivalent of a school year, in contrast to schools in Europe (such as Switzerland or Netherlands) closed only for about two months (Engzell et al., 2021; Schult et al. 2021). An average longer period of disruption to learning may be hypothesized to have had a more drastic effect on learning. Finally, mathematics learning is often shown to suffer more during summer and school absences compared to reading (Locke et al., 2021), perhaps because children are more likely to have some exposure to reading in their daily home lives. Therefore, it may be hypothesized that without consistent mathematics instruction through school, students are more likely to lose more learning in mathematics, compared to reading.

2.2. Analytic Plan

Effect sizes were calculated as the difference between adjusted posttest scores for treatment (cohort 2020/2021) and control (cohort 2019) students, divided by the unadjusted standard deviation of the control group. Alternative procedures were used to estimate effect sizes when adjusted posttests or unadjusted standard deviations were not reported, as described by Lipsey and Wilson (2001). Mean effect sizes across studies and programs were calculated using an inverse variance approach (Lipsey & Wilson, 2001), adjusted for clustering as described by Hedges (2007). We used a multivariate meta-regression model with robust variance estimation (RVE) to conduct the meta-analysis (Hedges et al., 2010). In meta-regression, a random effects model was adopted since there was no single true effect size but a range of effect sizes that may have depended on other factors (Borenstein et al., 2010). We also conducted marginal means analysis to understand the mean value for each sub-group to gain more insights.

When we analyzed the data, we included four moderators: 1) grade, 2) country (U.S. or Non-U.S.), 3) subject (math and reading) and 4) test types (standardized testing vs. benchmark testing vs. formative testing vs. computer adaptive testing). Standardized assessments included tests such as the Progressive Achievement Tests or the Italian National Institute for Evaluation of Education System (INVALSI) assessment. Benchmark testing included assessments such as DIBELS and Progress in International Reading Literacy Study (PIRLS). Formative assements included i-Ready or STAR Math and Reading assessments, while computer-adaptive testing included Students in Kindergarten through Grade 2 were coded as “lower grade,” students in Grades 3-6 were coded as “middle grade,” and students in Grades 7-12 were coded as “upper grade.” If results were reported in combinations of grade level categories (for instance, Grades K-6), then they were coded as “mixed grade.”

All analyses were conducted in RStudio Version 1.4.1717 (RStudio Team, 2021) using the R project for statistical computing Version 4.1.1 (R Core Team, 2021). We cleaned data using readxl (Wickham & Bryan, 2019), janitor (Firke, 2021), tidyr (Wickham, 2021), tidyverse (Wickham et al., 2019), plyr (Wickham, 2011) and dplyr (Wickham, 2018); conducted meta-analyses using metafor (Viechtbauer, 2010) and clubSandwich (Pustejovsky, 2021); and produced tables and figures with flextable (Gohel, 2021), officer (Gohel, 2021), tableone (Yoshida & Bartel, 2021), and ggplot2 (Wickham, 2016). To assess publication bias, this study adopted selection modeling instead of other traditional methods (e.g., funnel plot, Egger’s regression, fail-safe N) because of the limitations in these traditional techniques. Selection modeling involves a model of the selection process that uses a weight function to estimate the probability of selection in random-effect meta-analysis (Hedges, 1992). Selection modeling is the most recommended method to investigate meta-analyses’ publication bias (Terrin et al., 2005). This study used weightr package (Coburn & Vevea, 2019) to apply the Vevea and Woods’ (2005) weight-function model.

2.3. Data Collection

A broad literature search was conducted to locate as many studies that might meet the inclusion criteria as possible. The article search started in March 2021 and ended in July 2022. We searched on *Google Scholar* and other internet search engines and educational publisher websites for both published and unpublished reports. Due to the novelty of this research, we also read opinion and news articles from major education news channels for latest research updates and references to recent studies on the topic of COVID learning loss, such as Education Week, The 74, and Hechinger Report. Authors' internal networks of colleagues and fellow researchers, and audience inputs during presentations of this work, also contributed to the iterative process of refining the article search strategy. Our search keywords include "COVID/Coronavirus Learning Loss/Gain," "COVID/Coronavirus Slide," "COVID learning lag," "COVID-19 slump," "COVID learning disruptions," "COVID unfinished learning,""COVID interrupted instruction" and "COVID/Coronavirus's Impacts on Students/Education." Our initial search returned hundreds of articles. We screened these articles based on the following six inclusion criteria to choose eligible studies to include in the meta-analysis. After eligible studies were identified and finalized, we used an online web-based tool called *Paperfetcher* (Authors, 2021) to conduct a backward snowballing search by screening the reference lists of included studies and other systematic reviews on this topic (including Donnelly & Patrinos, 2021 and Hammerstein et al., 2021).

2.4. Inclusion Criteria

The inclusion criteria used are:

1. Provide enough quantitative information on student achievement outcomes (in subjects such as mathematics or literacy) to compute effect sizes. For example, Spitzer and Musslick (2021) was excluded because they report error rate, instead of effect size, in standardized deviations.

   a. This could take the form of standardized assessments, such as Amplify or DIBELS, for instance.
   b. For articles with insufficient information, we emailed corresponding authors for additional details. Some studies, such as Tomasik et al. (2021) were excluded in this procedure because the authors did not respond.
   c. Qualitative studies using interviews, surveys, and descriptive statistics were excluded.
2. Use real data collected at least partly during the pandemic to compute learning loss. Studies must include one data point from prior to the pandemic (i.e., Fall 2019) as a baseline point. Studies that predict potential COVID learning loss were excluded. For example, Kuhfeld et al. (2021) used summer loss projections to predict learning loss during COVID, and was therefore excluded. Kilbride et al. (2022) was excluded because…
3. Focus on K-12 school grades. For instance, we excluded Blagg (2021) because of its focus on adult outcomes.
4. Be available to the public, including both published and unpublished studies. Some potential studies were abandoned because of limited accessibility. For example, Carpenter (2020) was ruled out due to accessibility problems.
5. Be available in English. This inclusion criterion ensures that each included study could be double coded independently by both authors. English is the common language between the two authors and double coding follows Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) standards for high quality systematic reviews. For instance, Depping et al. (2021) was excluded because the text was written in German.

3. Results

3.1. Descriptive results

After a comprehensive search and application of the inclusion criteria, we identified 30 eligible studies with 262 effect sizes. Table 1 presents descriptive statistics of included studies. Almost half of the studies (n = 14) were conducted in the U.S. Among the 262 effect sizes, 48.1% reported math outcomes and 51.1% reported reading outcomes; 34.0% reported outcomes in lower grade bands, 46.2% reported outcomes in middle grade bands, and 11.8% reported outcomes in upper grade bands; 57.3% were measured by computer adaptive testing and 20.6% were measured by standardized testing. Table 4 presents included studies' detailed characteristics, including study name, country, test name, subject or subjects tested, grade level, sub-group information (if applicable), and effect size reported or computed.

3.2 Meta-regression results

On average, our meta-regression results showed that students lost 0.20 (95% predictive interval: -0.450, 0.044) standard deviations of learning during the pandemic school closures while holding all moderators fixed at their mean. Table 2 presents the meta-regression results derived from quantitative data analysis in R. This result is statistically significant at 0.01 significance level ($p < 0.01$). In the meta-regression, we included four moderators: subject (reading or math), grade band (lower, middle, mixed or upper), country (US or non-US) and test-type (standardized testing, benchmark testing, formative testing, and computer adaptive testing). Test-type is a significant moderator at 0.06 significance level ($p = 0.054$).

3.2.1 Subject: math vs. reading

No significant difference was found between the mean effect size of math and reading outcomes. Compared to students' math achievement, students' reading achievement is somewhat more negatively affected (ES = -0.01). On average, reading outcomes suffered a statistically significant mean effect size (ES = -0.21, p = .004) of loss, compared to math outcomes with a significant mean effect size of -0.20 (p = .022).

3.2.2 Grade level: lower vs. middle vs. upper

No significant difference was found between the mean effect size among the three grade levels. Compared to lower grade levels, students in middle and upper grades are somewhat more negatively affected (ES = -0.01). On average, students in lower grades experienced a statistically significant mean effect size (ES = -0.20, p = .01) of learning loss, compared to students in middle grades with a significant mean effect size of -0.24 (p = .002) and students in upper grades with a significant mean effect size of -0.18 (p = .014).

3.2.3 Country: US vs. non-US

No significant difference was found between the mean effect size in the US and other countries. Compared to students in other comparable countries, students in the US are somewhat more negatively affected (ES = -0.12). On average, students in the US experienced a marginally statistically significant mean effect size (ES = -0.23, p = .01) of learning loss, compared to students in other countries with a marginally significant mean effect size of -0.11 (p = .089).

3.2.4 Test type: standardized testing vs. benchmark testing vs. formative testing vs. computer adaptive testing

Significant difference was found between the mean effect sizes measured by four types of assessments. On average, outcomes measured by standardized testing was found to have a marginally statistically significant mean effect size (ES = -0.17, p = .004), compared to outcomes measured by benchmark testing with a non-significant mean effect size of -0.22 (p = .114), compared outcomes measured by formative testing with a non-significant mean effect size of -0.05 (p = .400), and outcomes measured by computer adaptive testing with a non-significant mean effect size of -0.08 (p = .165).

3.3 Interactions

The interaction analysis identified a significant differential effect for subject outcomes by grade bands (ES = -0.04, p = .046).On average, for reading outcomes, effect sizes are higher for lower grades (ES = -0.21, p = .005), as compared to middle grades (ES = -0.20, p = .003) and upper grades (ES = -0.15, p = .016). On average, for math outcomes, effect sizes are higher for middle grades (ES = -0.30, p = .001), as compared to upper grades (ES = -0.23, p = .019) and lower grades (ES = -0.19, p = .018).

3.4 Publication bias

Applying Vevea and Woods' weight-function model, this study found significant publication bias. Likelihood ratio test for the model result is significant (x squared = 9.25, p < .01). This means that the estimated pooled effect of school-based programs are potentially inflated by the exclusion of missing studies from the current meta-analysis. Non-significant and positive findings are 2.56 times as likely to be included as significant ones.

4. Discussion

Our analysis of student learning losses points to an average loss of 0.20 standard deviations (*p* = 0.006) since the pandemic closed schools, with losses of 0.43 standard deviations in reading and 0.41 standard deviations in mathematics. The meta-regression results also suggest several possible trends in learning loss for different subgroups including more serious learning losses for younger children, those within the United States, and in reading, though these findings were not statistically significant. The results also pointed to differences due to different means of measuring losses, with students demonstrating greater loss when assessed using standardized assessments (such as the Ohio Third-Grade English Language Arts assessment or the Italian National Institute for Evaluation of Education System (INVALSI) assessment) and benchmark assessments (such as DIBELS or PIRLS), in comparison to formative assessments (i.e., i-Ready) or computer adaptive assessments (NWEA MAP).

The serious overall learning loss due to the pandemic found by our study, as well as the trends in learning loss suggested by our metaregression and marginal means analyses, point to real world implications for educational practice and policy. Education systems and school districts require ongoing support to provide services needed to assist students in recovering their learning losses. Evidence-based interventions, such as targeted paraprofessional-led tutoring programs for students at all age and grade levels, have been proven to lead to large and significant learning gains for students in reading and mathematics (Baye et al., 2019; Neitzel et al., 2021; Slavin et al., 2009; Slavin et al., 2011), contributing to sustainable recovery.

While these results are striking and concerning, they only likely tell a portion of hte full picture of the ongoing effect of the COVID-19 pandemic on student learning progress. The students measured in the studies included in this meta-analysis may not be representative of the entire student population. Given the disparate access to distance learning, a non-random group of students who experienced more pandemic-related hardships may have missed school assessments during the pandemic. Access to remote learning was inequitable, with students from marginalized populations, those from lower-SES families and communities, and special education students, all less likely to be able to access education consistently during the pandemic (Allen et al., 2021; Fox et al., 2021; Tienken, 2020; "Special Education in the Era of COVID-19", 2021). This may be considered a potential limitation of this paper, but is related to the studies that are of necessity part of the analysis. Students absent from or non-randomly part of the testing programming would in turn lead to missing data in the included studies, and introduce potential bias due to the non-random nature of the missing data. This suggests that while the learning loss was indeed high and statistically significant, it may in reality have been underestimated due to the exclusion of underserved populations in school assessments.

On a policy level, these students must be reincluded in the education system and provided with the academic and non-academic support they require. Given the widespread effects of the pandemic, it will continue to be necessary to take specific measures to treat and reengage with struggling students, who may be experiencing lasting physical or mental trauma. These efforts have begun in much of the country, but analysts have also found that much of the COVID-19 recovery money allocated to education through the America Rescue Plan has not been spent (Lumpkin & Jayaraman, 2022), suggesting that much more could be done to address learning recovery and other student needs in response to the pandemic.

It is also important to consider how we are assessing students and to what ends those assessments are used. Students in these studies performed worse in standardized assessments and benchmark testing. This is a good reminder that standardized tests, often longer and more high-stakes forms of assessing students, may not be the most useful form of assessing student progress. As the return to in-person schooling continues, it will be important for school districts to reconsider the ways that they effectively measure student progress, what the most meaningful methods are for teachers to use in adapting their instruction, and who is left out of or poorly represented by certain assessment formats.

Our findings are in agreement with other reviews and studies on learning loss. Hammerstein et al. (2021) qualitatively summarizes learning loss in elementary and secondary students, concluding that younger students and students coming from lower SES backgrounds are affected more compared to their counterparts. Similarly, in their qualitative review of COVID learning loss research, Donnelly and Patrinos (2021) concluded that the majority of studies indicated student learning loss in a variety of subjects, ages, and geographical locations, while half of their included studies indicated increased inequality in learning.

As this is a new and ongoing area of research, the results from this study reflect only shorter-term impacts of the pandemic on students' academic learning in mathematics and reading (through Fall 2021 at the latest), as that is what the current literature can tell us at this point. As our measurement and understanding of student learning in the aftermath of the pandemic evolves, it will be important to develop a detailed analysis of the long-term effects of the pandemic. The effects of school closures and disrupted learning may persist in unexpected ways, schools may close again due to unexpected variances or in response to new disease outbreaks (such as the delta and omicron variants did), while lingering effects of coronavirus (such as what is being termed “long COVID”) may continue to impact student learning progress.

The statistical power of this study was limited by the small sample size available. As only 16 studies met our inclusion criteria, and were included in the analysis, our statistical power and ability to make causal inferences is limited. This may be one explanation for the lack of significance in the identified moderators. As more studies and research on COVID learning loss are published and data are released, we plan to review, revise, and incorporate additional findings in our research, improving our sample and statistical power.

Future research should build on current results by incorporating newly published and released research concerning longer-term COVID learning effects. With additional studies included in the meta-regression analysis, additional informative moderators (e.g.,SES status, gender) could be added into the equation to conduct more detailed analyses. These moderators were not able to be systematically applied here, and were thus excluded. In addition, to expand from our limited scope on K-12 students, future research could shift the focus to postsecondary education and potentially compare results.

Moreover, our meta-analysis focuses on reading and math due to the prevalence of standardized assessments in these subjects across grades. To build on this work, researchers could try to include measurements of additional academic subjects (such as science) or non-academic skills to assess the impact of the pandemic in a more holistic way.

Finally, researchers should also seek to disseminate the results in ways that are transferable and practically useful for school districts and administrators preparing for school reopening and remedial education in Fall 2022. In particular, analysis of COVID learning loss should seek to capture learning for those students that have heretofore been excluded from COVID learning studies, in order to provide greater information and direction in targeting educational recovery and remedial education programs best designed to reach those most in need of additional literacy, mathematics, and social-emotional support as schools seek to reopen.

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Appendix

Table 1

Descriptive Statistics of Included Studies

Category	Level	Overall
		Study Level
Total Studies		30
Country	Australia	1 (0.03)
Country	Belgium	2 (0.07)
Country	Germany	2 (0.07)
Country	Italy	1 (0.03)
Country	Denmark	1 (0.03)
Country	Spain	1 (0.03)
Country	Brazil	1 (0.03)
Country	Netherlands	4 (0.13)
Country	UK	3 (0.1)
Country	USA	14 (0.47)
		Outcome Level
Total Effect Sizes		262
Subject	Math	126 (48.1)

Subject	Reading	134 (51.1)
Subject	Others	2 (0.8)
Grade band	Lower	89 (34.0)
Grade band	Middle	121 (46.2)
Grade band	Mixed	21 (8.0)
Grade band	Upper	31 (11.8)
Test type	Standardized testing	54 (20.6)
Test type	Benchmark testing	10 (3.82)
Test type	Formative testing	48 (18.3)
Test type	Computer adaptive testing	150 (57.3)

Note. Percentages in brackets.

Table 2

Meta-regression Results for Included Studies

Coefficient	beta	se	t	df	p
Null Model					
Intercept	-0.12	0.02	-6.71	26.41	<0.001
Meta-Regression					
Intercept	-0.20	0.06	-3.51	9.22	0.006
Mathematics	0.01	0.06	0.23	9.19	0.822
Grade Band	-0.01	0.02	-0.77	9.11	0.462
US	-0.12	0.08	-1.41	10.63	0.186
Test Type	0.03	0.02	2.17	10.21	0.054
Mathematics.c * Grade.band	-0.04	0.02	-2.23	11.72	0.046
Grade.band * US.c	0.01	0.03	0.38	12.20	0.711
Mathematics.c * Test.type	0.02	0.01	1.24	7.97	0.251

Note. se = standard error, t = t statistics, df = degree of freedom, p = p value. . $p < .1$ * $p < .05$. ** $p < .01$. *** $p < .001$

Table 3

Marginal Means

Moderator	Group	beta	SE	t-statistic	p	df
(Mathematics)	0	-0.43	0.06	-3.71	0.004	10.56
	1	-0.41	0.07	-2.70	0.022	10.09
(Grade Band)	1	-0.41	0.06	-3.26	0.010	8.61
	2	-0.50	0.05	-4.67	0.002	7.93
	3	-0.37	0.06	-3.15	0.014	7.64
	4	-0.52	0.07	-3.41	0.007	9.92
(US)	0	-0.22	0.06	-1.94	0.089	7.83
	1	-0.47	0.07	-3.28	0.010	8.60
(Test Type)	1	-0.34	0.04	-3.82	0.004	9.35
	2	-0.44	0.08	-2.63	0.114	2.08
	3	-0.10	0.05	-0.89	0.400	8.19

	4	-0.15	0.05	-1.58	0.165	6.05
(Mathematics* Test Type)	0 1	-0.34	0.04	-4.48	0.001	11.93
	0 2	-0.52	0.06	-4.07	0.062	1.86
	0 3	-0.11	0.06	-0.92	0.381	8.38
	0 4	-0.22	0.04	-3.02	0.025	5.79
	1 1	-0.30	0.07	-2.23	0.054	8.64
	1 2	-0.19	0.06	-1.40	0.210	6.30
	1 3	-0.07	0.05	-0.50	0.634	7.12
	1 4	-0.07	0.07	-0.52	0.624	5.91
(MathematicsX Grade.band)	0 1	-0.21	0.06	-3.58	0.005	9.53
	0 2	-0.20	0.05	-4.13	0.003	8.42

	0 3	-0.15	0.05	-3.05	0.016	7.91
	0 4	-0.22	0.07	-3.13	0.010	11.06
	1 1	-0.19	0.07	-2.87	0.018	9.35
	1 2	-0.30	0.06	-4.85	0.001	8.61
	1 3	-0.23	0.08	-2.92	0.019	8.02
	1 4	-0.29	0.08	-3.56	0.005	10.76
(Grade.bandXUS)	1 0	-0.16	0.05	-3.45	0.026	4.05
	1 1	-0.22	0.07	-3.19	0.013	7.96
	2 0	-0.13	0.04	-3.42	0.006	10.56
	2 1	-0.28	0.06	-4.46	0.003	7.47
	3 0	-0.19	0.17	-1.14	0.391	1.70
	3 1	-0.20	0.06	-3.22	0.014	7.31
	4 0	-0.21	0.05	-4.25	0.004	7.20

	4 1		-0.26	0.08	-3.20	0.013	7.95

Table 4

Included Studies' Detailed Characteristics

Study	Country	Published	Test	Subject	Grade.s	Effect.Size
Amplify (2021)	USA	0	DIBELS 8	Reading	K-1	-0.51
			DIBELS 8	Reading	K-1	-0.56
			DIBELS 8	Reading	K-1	-0.39
			DIBELS 8	Reading	K-1	-0.2
			DIBELS 8	Reading	K-1	-0.18
			DIBELS 8	Reading	K-1	-0.17
Arenas & Gortazar (2022)	Spain	0	External diagnosis assessment from The Basque Institute for Research and Evaluation in Education	Math	4,8	-0.075

			External diagnosis assessment from The Basque Institute for Research and Evaluation in Education	Reading	4,8	-0.05
			External diagnosis assessment from The Basque Institute for Research and Evaluation in Education	Reading	4,8	0

Bazoli et al. (2022)	Italy	0	Italian National Institute for Evaluation of Education System (INVALSI) assessment	Math	5-13	-0.142
			Italian National Institute for Evaluation of Education System (INVALSI) assessment	Math	5-13	-0.291
			Italian National Institute for Evaluation of Education System (INVALSI) assessment	Reading	5-13	-0.02

			Italian National Institute for Evaluation of Education System (INVALSI) assessment	Reading	5-13	-0.316
			Italian National Institute for Evaluation of Education System (INVALSI) assessment	Math	5-13	-0.273
			Italian National Institute for Evaluation of Education System (INVALSI) assessment	Reading	5-13	0.057

Betebenner & Van Iwaarden (2022)	USA	0	Rhode Island RICAS assessment	Math	3-8	-0.16
			Rhode Island RICAS assessment	Math	3-8	-0.4
			Rhode Island RICAS assessment	Reading	3-8	-0.11
			Rhode Island RICAS assessment	Reading	3-8	-0.14
			Rhode Island RICAS assessment	Math	3-8	-0.28
			Rhode Island RICAS assessment	Math	3-8	-0.31
			Rhode Island RICAS assessment	Reading	3-8	-0.18
			Rhode Island RICAS assessment	Reading	3-8	-0.16

			Rhode Island RICAS assessment	Reading	3-8	-0.24
			Rhode Island RICAS assessment	Reading	3-8	-0.12
			Rhode Island RICAS assessment	Math	3-8	-0.38
			Rhode Island RICAS assessment	Math	3-8	-0.32
Bielinski et al. (2020)	USA	0	computer-adaptive assessment	Math	K-5	-0.16
			computer-adaptive assessment	Math	K-5	-0.21
			computer-adaptive assessment	Math	K-5	-0.16
			computer-adaptive assessment	Math	K-5	-0.21
			computer-adaptive assessment	Reading	K-5	-0.07

			computer-adaptive assessment	Reading	K-5	-0.13
			computer-adaptive assessment	Math	K-5	-0.12
			computer-adaptive assessment	Reading	K-5	-0.15
			computer-adaptive assessment	Reading	K-5	-0.11
			computer-adaptive assessment	Math	K-5	-0.24
			computer-adaptive assessment	Math	K-5	-0.11
			computer-adaptive assessment	Reading	K-5	-0.12
			computer-adaptive assessment	Reading	K-5	-0.13
			computer-adaptive assessment	Reading	K-5	-0.08
			computer-adaptive assessment	Reading	K-5	-0.15

			computer-adaptive assessment	Math	K-5	-0.05
Birkelund & Karlson (2021)	Denmark	0	Danish national test score	Reading	2-8	0
Blainey & Hannay (2021)	UK	0	Standardized test	Math	1-6	-0.06
			Standardized test	Math	1-6	-0.09
			Standardized test	Reading	1-6	-0.07
			Standardized test	Reading	1-6	-0.14
			Standardized test	Reading	1-6	-0.05
			Standardized test	Math	1-6	-0.04
			Standardized test	Math	1-6	-0.09
			Standardized test	Reading	1-6	-0.01
			Standardized test	Math	1-6	-0.02
			Standardized test	Math	1-6	-0.09
			Standardized test	Reading	1-6	-0.01
			Standardized test	Reading	1-6	-0.01

Dawson (2022)	USA	0	i-Ready	Reading	K-8	0
			i-Ready	Reading	K-8	-0.1
			i-Ready	Math	K-8	-0.03
			i-Ready	Reading	K-8	0.09
			i-Ready	Math	K-8	-0.13
			i-Ready	Math	K-8	0
Dorn et al. (2021)	USA	0	i-Ready Math	Math	K-5	-0.02
			i-Ready Math	Math	K-5	-0.05
			i-Ready Math	Math	K-5	-0.09
			i-Ready Math	Math	K-5	-0.07
			i-Ready Math	Math	K-5	-0.09
			i-Ready ELA	Reading	K-5	-0.05
			i-Ready Math	Math	K-5	-0.11
			i-Ready Math	Math	K-5	-0.04
			i-Ready Math	Math	K-5	-0.08
			i-Ready Math	Math	K-5	-0.06
			i-Ready ELA	Reading	K-5	-0.07
			i-Ready Math	Math	K-5	-0.07

			i-Ready Math	Math	K-5	-0.06
			i-Ready Math	Math	K-5	-0.08
			i-Ready Math	Math	K-5	-0.04
			i-Ready Math	Math	K-5	-0.06
Engzell et al. (2020)	Netherlands	1	Biannual Dutch standardized test	Reading	4-7	-0.08
EPI (2021)	UK	0	STAR	Reading	4-6	-0.09
Gambi & de Witte (2021)	Belgium	0	standardised tests	Others	6	-0.15
			standardised tests	Math	6	-0.11
			standardised tests	Others	6	-0.08
			standardised tests	Reading	6	-0.23
Goldhaber et al. (May 2022a)	USA	0	NWEA MAP	Math	3-8	-0.2
			NWEA MAP	Reading	3-8	-0.1
Gore et al. (2021)	Australia	1	Progressive Achievement Tests in math	Math	3-4	-0.16

			Progressive Achievement Tests in math	Reading	3-4	-0.16
			Progressive Achievement Tests in math	Reading	3-4	0.15
			Progressive Achievement Tests in math	Math	3-4	0
			Progressive Achievement Tests in math	Reading	3-4	0
			Progressive Achievement Tests in math	Math	3-4	0.15
			Progressive Achievement Tests in math	Math	3-4	0
			Progressive Achievement Tests in math	Reading	3-4	0
Haelermans et al. (2022)	Netherlands	1	National standardized test scores	Reading	1-6	-0.14

			National standardized test scores	Math	1-6	-0.21
			National standardized test scores	Reading	1-6	-0.15
Kogan & Lavertu (2021)	USA	1	Ohio Third-Grade English Language Arts assessment	Reading	3	-0.23
Kogan 2022	USA	0	Ohio state assessment	Reading	3	-0.08
Kuhfeld et al. (2022)	USA	1	NWEA MAP	Reading	3-8	-0.19
			NWEA MAP	Math	3-8	-0.11
Lichand et al. (2022)	Brazil	1	Avaliações de Aprendizagem em Processo (AAPs)	Reading	6-12	-0.32
			Avaliações de Aprendizagem em Processo (AAPs)	Math	6-12	-0.32

Locke (2021)	USA	0	computer-adaptive assessments testing (CAT)	Reading	1-7	-0.21
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.22
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.23
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.1
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.18
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.24

			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.06
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.17
			computer-adaptive assessments testing (CAT)	Reading	1-7	0.08
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.09
			computer-adaptive assessments testing (CAT)	Reading	1-7	0.03
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.25

			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.12
			computer-adaptive assessments testing (CAT)	Reading	1-7	0.04
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.2
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.1
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.22
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.16

			computer-adaptive assessments testing (CAT)	Math	1-7	-0.07
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.21
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.22
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.25
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.18
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.09

			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.14
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.07
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.49
			computer-adaptive assessments testing (CAT)	Math	1-7	0.26
			computer-adaptive assessments testing (CAT)	Math	1-7	0.07
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.12

			computer-adaptive assessments testing (CAT)	Math	1-7	-0.3
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.2
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.11
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.13
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.09
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.16

			computer-adaptive assessments testing (CAT)	Math	1-7	-0.2
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.36
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.37
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.13
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.07
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.03

			computer-adaptive assessments testing (CAT)	Math	1-7	-0.29
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.02
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.28
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.39
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.16
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.06

			computer-adaptive assessments testing (CAT)	Math	1-7	0.06
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.24
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.09
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.16
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.26
			computer-adaptive assessments testing (CAT)	Math	1-7	-0.18

			computer-adaptive assessments testing (CAT)	Math	1-7	-0.21
			computer-adaptive assessments testing (CAT)	Reading	1-7	-0.21
Ludewig et al. (2022)	Germany	1	Progress in International Reading Literacy Study	Reading	4	-0.14
Maldonado & Witte (2020)	Belgium	1	Annual standardized test--French	Reading	6	-0.25
			Annual standardized test--Math	Math	6	-0.22
			Annual standardized test--Dutch	Reading	6	-0.26
Patarapichayatham et al. (2021)	USA	0	computer-adaptive assessments testing (CAT)	Reading	1-8	-0.19

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.28
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.17
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.22
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.22
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.26
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.22

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.21
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.14
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.24
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.24
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.23
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.14

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.19
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.31
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.33
			computer-adaptive assessments testing (CAT)	Reading	1-8	0.13
			computer-adaptive assessments testing (CAT)	Reading	1-8	0.02
			computer-adaptive assessments testing (CAT)	Reading	1-8	0

			computer-adaptive assessments testing (CAT)	Reading	1-8	0.07
			computer-adaptive assessments testing (CAT)	Math	1-8	0.19
			computer-adaptive assessments testing (CAT)	Math	1-8	0.04
			computer-adaptive assessments testing (CAT)	Math	1-8	0
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.28
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.24

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.2
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.19
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.33
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.1
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.1
			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.2

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.3
			computer-adaptive assessments testing (CAT)	Math	1-8	0.1
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.01
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.02
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.27
			computer-adaptive assessments testing (CAT)	Math	1-8	0.02

			computer-adaptive assessments testing (CAT)	Math	1-8	-0.07
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.13
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.08
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.01
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.1
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.16

			computer-adaptive assessments testing (CAT)	Math	1-8	-0.29
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.29
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.24
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.23
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.36
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.22

			computer-adaptive assessments testing (CAT)	Math	1-8	-0.17
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.17
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.52
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.28
			computer-adaptive assessments testing (CAT)	Math	1-8	-0.36
			computer-adaptive assessments testing (CAT)	Math	1-8	0.01

			computer-adaptive assessments testing (CAT)	Reading	1-8	-0.23
Pier et al. (2021)	USA	0	MAP ELA	Reading	4-9	-0.1
			MAP Math	Math	4-9	-0.06
			MAP Math	Math	4-9	-0.07
			STAR ELA	Reading	4-9	-0.11
			MAP ELA	Reading	4-9	-0.03
			STAR ELA	Reading	4-9	-0.06
			MAP Math	Math	4-9	-0.13
			STAR ELA	Reading	4-9	-0.1
			MAP ELA	Reading	4-9	-0.09
			STAR Math	Math	4-9	-0.08
			STAR ELA	Reading	4-9	-0.11
			MAP ELA	Reading	4-9	-0.06
			STAR ELA	Reading	4-9	-0.01
			STAR ELA	Reading	4-9	-0.01
			MAP ELA	Reading	4-9	-0.01
			STAR Math	Math	4-9	-0.2
			STAR Math	Math	4-9	-0.1
			MAP Math	Math	4-9	-0.14
			MAP ELA	Reading	4-9	-0.03
			STAR Math	Math	4-9	-0.19
Raymond et al. (2020)	USA	0	MAP Math	Math	1-5	-0.32

			MAP ELA	Reading	1-5	-0.21
Renaissance Learning (2020)	USA	0	STAR ELA	Reading	1-8	0.01
			STAR ELA	Reading	1-8	-0.02
			STAR MATH	Math	1-8	-0.05
			STAR ELA	Reading	1-8	-0.03
			STAR ELA	Reading	1-8	-0.02
			STAR ELA	Reading	1-8	-0.02
			STAR MATH	Math	1-8	-0.03
			STAR ELA	Reading	1-8	0.12
			STAR MATH	Math	1-8	-0.05
			STAR MATH	Math	1-8	-0.1
			STAR MATH	Math	1-8	-0.08
			STAR ELA	Reading	1-8	-0.01
			STAR MATH	Math	1-8	-0.12
			STAR MATH	Math	1-8	-0.16
			STAR ELA	Reading	1-8	-0.02
Rose et al. (2021)	UK	0	NFER standardized assessment	Reading	2	-0.17
			NFER standardized assessment	Math	2	-0.14

Schult et al. (2021)	Germany	0	Competence Assessment	Math	5	-0.03
			Competence Assessment	Math	5	-0.09
			Competence Assessment	Reading	5	-0.07
Schuurman et al. (2021)	Netherlands	1	National standardized test scores	Reading	3-5	-0.09
van der velde et al. (2021)	Netherlands	1	Program online performance assessment	Reading	7-10	0.25

Note. SES = socio-economic status; G = grade; ELA= English language arts.

Figure 1

PRISMA Flow chart

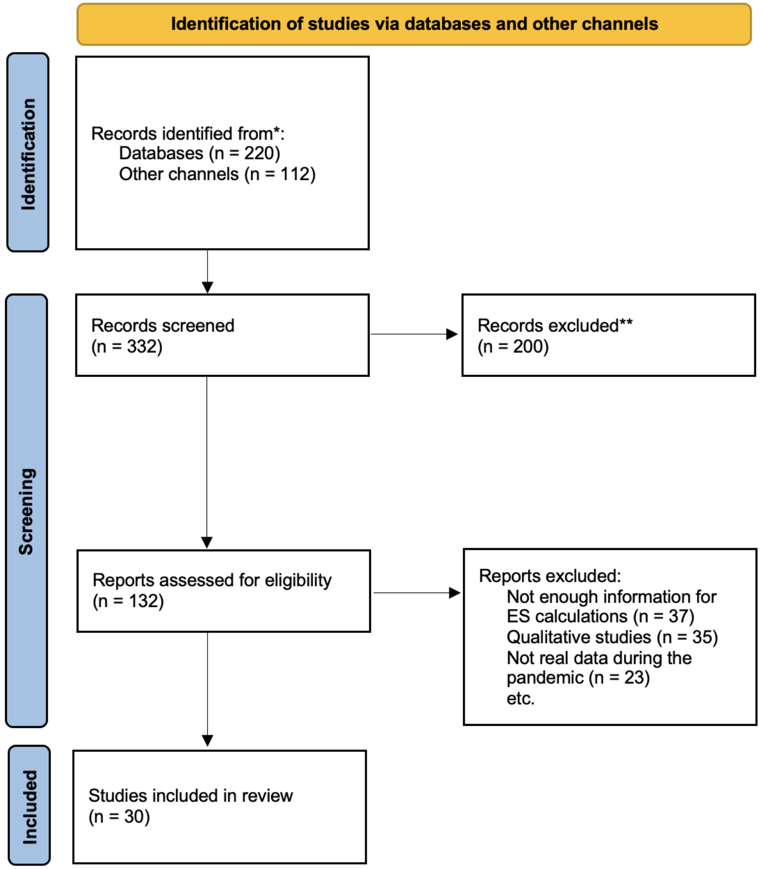

Figure 2
Distribution of Effect Sizes