Computers & Education 226 (2025) 105197

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

A meta-analysis on the effect of technology on the achievement of less advantaged students☆,☆☆

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ARTICLE INFO

Keywords:
Less advantaged students
Student achievement
Educational technology
Meta-analysis

ABSTRACT

This paper presents a meta-analysis that investigates the impact that the educational use of digital technologies has on less advantaged students' achievement. We use a comprehensive definition for this group of students that includes all students in less developed countries as well as more disadvantaged students in more developed countries. 740 estimates from 72 studies employing experimental and quasi-experimental research designs are collected. Overall, educational technology initiatives are found to have a small, positive, statistically significant effect that remains even after correcting for publication bias. Additionally, our results indicate that computer-assisted learning and behavioural interventions are more effective in raising the achievement of less advantaged students than simple access to technology. Interestingly, the effect of these two interventions appears to be of a similar magnitude. Finally, the use of digital technologies is associated with slightly greater achievements in math and science than humanities.

1. Introduction

The expansion of technology has affected many areas of our life, including education. Digital learning tools such as tablets, smartboards and online applications have become increasingly important elements of teaching and course delivery. There is a lot of evidence showing that the introduction of these tools can improve children's teaching and learning experiences. McEwan (2015) argues that technology-based interventions may be as effective in raising student achievement as well-known and popular policies such as smaller class size, teacher training and performance incentives.

Discussions exist in the literature concerning the relationship between digital technologies and equity in educational outcomes (Warschauer & Xu, 2018). On the one hand, there are concerns that more vulnerable students can miss out on the benefits that these technologies bring. The use of digital technologies may be less effective for low socio-economic status children as they tend to have

☆ The authors would like to thank three anonymous referees for their helpful and constructive comments. The usual disclaimer applies.☆☆ Jonatan Castaño Muñoz acknowledges the support of the 'Ramón y Cajal' grant RYC 2020-030157 funded by MCIN (Ministerio de Ciencia, Innovación y Univesidades)/AEI (Ministerio de Ciencia, Innovación y Univesidades)/10.13039/501100011033 and by "ESF Investing in your future", and the University of Seville "VI University research plan" (VI plan propio de investigación) for this work.

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[1] The views expressed are purely those of the author and may not in any circumstances be regarded as stating an official position of the European Commission.

https://doi.org/10.1016/j.compedu.2024.105197
Received 1 May 2024; Received in revised form 2 November 2024; Accepted 11 November 2024
Available online 13 November 2024
0360-1315/

limited access to technological infrastructure (Hohlfeld, Ritzhaupt, Barron, & Kemkerhon, 2008), exhibit moderate levels of digital competence (Fraillon, Ainley, Schulz, Friedman, & Duckworth, 2019), can count on little external support for the use of these technologies (Reich, 2020), and are less likely to adopt a self-regulated learning strategy (Yang, Cheng, & Chen, 2018).

On the other hand, however, other arguments suggest that the application of technology to the education sector has the potential to be very beneficial to more disadvantaged students. First, technology may enable personalised learning by tailoring educational experiences to individual students' needs and abilities. This may be advantageous especially for students who need extra help (e.g., students with learning difficulties), ensuring that they receive the support that is right to them and empowering them to choose when and how they learn (Ogan et al., 2012; Wagner, 2016). Second, the incorporation of technologies into the learning process may increase student engagement. Interactive and multimedia-rich digital resources (that include, for instance, games, simulation, quizzes) may make learning enjoyable and exciting, doing a better job in capturing students' attention than traditional classroom settings. Students lacking motivations, who are more likely to come from less advantaged backgrounds (Fejes, 2012), may particularly benefit from this learning approach. Third, technology has broken down physical barriers, enabling learners to have access to high-quality educational resources irrespective of their geographical location (e.g., through online learning platforms, video conferencing tools). This is especially relevant for individuals from remote and rural areas who tend to face significant more challenges in obtaining learning materials than those from urban areas.

Given the growing importance of technologies in education, one needs to gain a better understanding of their role in enhancing the achievement of all students. It is important to know that the development and diffusion of digital technologies is not leaving behind those from more vulnerable groups. The purpose of this review is to analyse evidence from rigorous evaluations on the effect of educational technology (ed-tech) interventions on the academic performance of less advantaged students.

1.1. Prior reviews on technologies and the achievement of less advantaged students

Earlier reviews attempting to summarise existing evidence on the impact of digital technologies on the achievement of less advantaged students have followed two different approaches.

First, a few meta-analyses and systematic reviews have investigated how ed-tech interventions affect the learning outcomes of students in disadvantaged contexts such as less developed countries. Some of these studies have focused their attention on the impact of a specific set of technologies. For instance, Major, Francis, and Tsapali (2021) have looked at the effect of technology-supported personalised learning on academic outcomes for school-aged learners in low- and middle-income countries. They found that these interventions have a statistically significant positive effect on students' learning, reporting an overall effect size of 0.18. Other studies have adopted a broader approach, considering all types of technologies. For example, Rodriguez-Segura (2022) has attempted to synthetise the results of studies analysing the effect of any type of ed-tech intervention on student performance in less developed countries. He observes that, while access to technology interventions alone are not sufficient to enhance learning, interventions centred around self-led learning and improvements in instruction are the most promising ones.

The second line of research consists in meta-analyses on the association between ed-tech and student achievement in which socio-economic status is used as a moderator variable. For instance, Cheung and Slavin (2012 & 2013) consider K-12 students in the US and examine whether there any differences in the impact of technology on student performance in reading and math between students from high and low socio-economic status. No statistically significant differences across socio-economic status were found.

1.2. The current study

The present meta-analysis investigates the impact of ed-tech interventions on academic outcomes among less advantaged students. We extend previous relevant work by employing a comprehensive definition for this group of students that comprises all students in less developed countries as well as more disadvantaged students in more developed countries.

To the best of our knowledge, there is no meta-analysis examining the impact of digital technologies on the achievement of more disadvantaged students in more developed countries. This is important because, in contrast to earlier meta-analyses including socio-economic status as a moderator variable and thereby employing more privileged students as a control group, we use similar students (i.e., students from more disadvantaged backgrounds not being exposed to the ed-tech intervention) as a comparison group. In addition to studies where the majority of the sample or the whole sample consist of more disadvantaged students in more developed countries, we also consider studies analysing students in less developed countries. This allows us to take a holistic approach for the more disadvantaged students. Analysing and comparing results from the aforementioned two groups of studies is indeed an important value added of our research as this may provide information on differential returns to investment in ed-tech in different parts of the world. In less developed countries ed-tech may help to address issues such as low supply of qualified teachers, teachers' absenteeism,[2] scarce quality learning materials, and large student-to- teacher ratios,[3] but it may also play an important role in more developed countries, for instance by enhancing the quality of education for students from rural areas, boosting students' motivation, and personalising teaching practices (Escueta, Nickow, Oreopoulos, & Quan, 2020).

[2] Chaudhury, Hammer, Kremer, Muralidharan, and Rogers (2006) observe that in less developed countries the proportion of absent teachers during unannounced visits is 19%.

[3] For instance, according to the UNESCO database, while in 2018 the pupil-teacher ratio in primary education was 15.3 in OECD countries, the similar figure in the least developed countries (following the United Nations' definition) was 37.2.

Since the terms “more developed” and “less developed” countries have been used loosely in the literature, it is important to provide a working definition of these terms. In this review, “more developed” countries refer to high-income or upper middle-income countries as defined by the World Bank (WB)’s classification of countries by income levels. “Less developed” countries refer to low-income or lower middle-income countries, again as defined by the WB’s classification of countries by income levels.

Similarly, it is also important to provide a working definition of the expression “educational technology”. This refers to those digital tools and resources designed to deliver learning materials, support or enhance student achievement that complement, and not replace, in-person teaching (e.g., computer games, learning software, apps, text messages). Fully online courses as well as teacher-focused tools (e.g., learning analytics, AI for resource generation) are excluded.

This meta-analysis seeks to address the following three research questions (RQ).

RQ1. What is the overall impact of ed-tech interventions on the academic performance of this broader group of less advantaged students?

RQ2. Is the impact of ed-tech interventions on achievement different between all students in less developed countries and more disadvantaged students in more developed countries?

RQ3. What type/s of ed-tech interventions is/are more successful in raising the achievement of this broader group of less advantaged students?

2. Data and methods

2.1. Inclusion and exclusion criteria

Table 1 shows the ten predefined inclusion and exclusion criteria developed and applied in the screening process. We chose to consider the period from 2000 onwards because digital education gained momentum at the start of the millennium. According to a KPMG report (Wildi-Yune & Cordero, 2015), the global e-learning market has massively grown since 2000. Following the recommendations by the Cochrane Statistical Methods Group,[4] studies have not been excluded purely based on the sample size[5] (Grainge, 2015). In addition to peer-reviewed journal articles and scholarly book chapters, we decided to consider also conference papers, reports and working papers. The rationale behind this is to have a balanced picture of available evidence given that the grey literature represents an important vehicle for disseminating studies with null or negative results that might not otherwise be disseminated (Paez, 2017). We only included studies presenting evidence from experimental or quasi-experimental research designs. These techniques, which test causal hypotheses (White & Sabarwal, 2014), provide the more rigorous evidence for the evaluation of ed-tech on student academic outcomes. We restricted our attention to studies focusing on primary (including kindergarten), lower and upper secondary education and using objective indicators to measure student academic outcomes. Achievement in all subjects (except for digital literacy[6]) is considered.

2.2. Literature search

Studies included in our meta-analysis are identified through three main steps: 1) electronic database search, 2) ancestry search across the studies selected at the end of the first step, and 3) ancestry search across previous relevant systematic reviews and meta-analyses.

In the first step, following the recommendation that meta-analyses and systematic reviews should employ multiple bibliographic databases to search for relevant literature (Harari, Parola, Hartwell, & Riegelman, 2020), we used four of them (i.e., Web of Science, Scopus, Education Information Research Center (ERIC) and Google Scholar). Ewald et al. (2022) find that searching two or more databases reduces the risk of missing eligible studies and Hernandez, Marti, and Roman (2020) suggest that at least three search engines should be utilised. While ERIC is an education-focused database, Web of Science and Scopus are comprehensive general databases covering high-quality publications (Fan & Beh, 2023). Borrego and Froyd (2014) stress the importance of using general databases in addition to subject-specific ones when carrying out systematic reviews. The rationale for this is that research on a given topic of interest is often not only published in specialist journals or report series, but also in generalist journals or report series. Additionally, it is important to use Google Scholar as this database can be useful for finding grey literature (Haddaway, Collins, Coughlin, & Kirk, 2015).

Appendix A sets out the clusters of keywords used to identify the studies to be included in this meta-analysis. These studies were found using keywords covering five different concepts: (1) the setting of interest (kindergarten, primary and secondary education), (2)

[4] Its members were polled about whether it is appropriate for a Cochrane systematic review to exclude small studies. 26 out of 26 representatives voted against this proposal.

[5] While some previously published meta-analyses (e.g., Zhang et al., 2020) do not consider studies with a sample size of less than 5, this exclusion criterion is also met in our case (in our meta-analysis the study by Aunio and Mononen (2018) has the lowest sample size, i.e., 22).

[6] This is because digital competences are not always included among the basic skills expected to be learned by students. For instance, in PISA (Programme for International Student Assessment) basic skills are reading, mathematics and science. While reading in primary grades refers especially to vocabulary acquisition and text comprehension, in the intermediate and upper grade levels factual knowledge and understanding are progressively expanded and increasingly applied to operational use.

Table 1
Inclusion and exclusion criteria.

Criterion	Included	Excluded
Language	English	Other languages, e.g. Spanish, German, French, Portuguese
Data on an effect size or sufficient information to calculate it	Data on an effect size (or sufficient information to compute it) and its standard error (or *t*-statistic, or *p*-value, or sufficient information to calculate it)	Lack of data on an effect size (or insufficient information to compute it) or its standard error (or *t*-statistic, or *p*-value, or insufficient information to calculate it)
Publication type	Peer-reviewed journals, scholarly book chapters, conference papers, reports or working papers published between 2000 and 2023	Master's and PhD dissertations as well as peer-reviewed journals, scholarly book chapters, conference papers, reports or working papers published earlier than 2000 and later than 2023
Measurement of student achievement	Objective indicators including standardized test scores as well as scores from tests developed by teachers or researchers	Achievements in digital literacy, student's self-assessed grades, non-cognitive skills, and other outcomes (e.g., school attendance)
Education context	Primary (including kindergarten), lower and upper secondary education	Higher education
Research design	Experimental (i.e., randomized controlled trials (RCTs)) or quasi-experimental (i.e., pre-test post-test study, regression discontinuity, instrumental variable, propensity score, difference in differences) research designs	Non-experimental research designs
Research setting	Clear distinction between a treated group (exposure to ed-tech intervention) and a control group (no exposure to ed-tech intervention)	Comparison of two alternative treatments within the treated group
Disadvantaged context	Evidence from: countries classified by the WB as high- or upper-middle income countries at the time of the ed-tech intervention and where, following the approach of Dietrichson, Klint Jørgensen, and Filges (2017), at least 50% of the sample participants are from disadvantaged backgrounds defined in terms of parental occupation, education or income, access to free or reduced school meals, area of residence (e.g., rural or remote areas, low-income regions), migrant or minority status or countries classified by the WB as low- or lower-middle income countries at the time of the ed-tech intervention	Evidence from countries classified by the WB as high- or upper-middle income countries at the time of the ed-tech intervention not focusing on more disadvantaged students or focusing on low-performing students or students with learning problems but with no information on their socio-economic background
Definition of educational technology intervention	Interventions explicitly aiming at improving student achievement through the use of technologies. They should complement in-person learning and not fully replacing it	Interventions consisting of courses entirely delivered online
Sample size	Any sample size	

the methodology (experimental and quasi-experimental research designs), (3) the exposure (ed-tech interventions), (4) the outcome (student achievement), and (5) the socio-economic condition (more disadvantaged status). We employed Boolean terms 'OR' and 'AND' to combine searches within and between concepts, respectively. In ERIC, the search terms were searched in the 'abstract' and 'descriptor'. As regards Google Scholar, we searched 'with all of the keywords, anywhere in the article' and focused our attention on the first 100 results of the search (Romanelli et al., 2021). In Scopus, the search terms were sought in the 'title', 'abstract' and 'keywords'. In Web of Science, the search terms were sought only in the 'abstract'. Our search, which ended in December 2023, delivered 141 hits. After removing duplicates (i.e., 5), the two authors, working independently, screened the titles and the abstracts of the studies. Following this, 105 items were excluded. Next, the full text of the remaining 31 studies was retrieved and carefully examined. This exercise was again conducted by both authors who independently classified the studies as relevant and irrelevant based on the predefined inclusion and exclusion criteria. While internal consistency was quite strong (Cohen's Kappa was 0.88), studies on which there was disagreement were discussed in depth until consensus was reached. 11 studies were found as a result of this first step.

In the second step, we screened the references sections of the 11 studies selected in the first step with the purpose of finding additional studies (Byron & Post, 2016). Employing the ancestry approach, 10 relevant studies were added.

Finally, in the third step we expanded results from first two searches by reviewing the bibliographies of previous relevant systematic reviews and meta-analyses.[7] 51 relevant studies were identified through this additional ancestry search.

Since the number of relevant studies found through ancestry searches is significantly higher compared to the set of papers retrieved by the search in electronic databases, following the approach of Wilke and Pyka (2024), we performed some amendments to the list of keywords displayed in Appendix A. However, this did not lead to the inclusion of any additional relevant study, but only increased the number of irrelevant papers. The importance of using other sources of information in addition to electronic databases when conducting reviews on the topic of education and technology has been highlighted by Escueta et al. (2020) and Rodriguez-Segura (2022). Furthermore, in our case an additional difficulty lies in the identification of studies in more developed countries focusing on students with disadvantaged backgrounds. This is particularly challenging given that information about students' socio-economic conditions is often not included in the studies' titles, keywords and abstracts.

[7] These studies were selected among those excluded in the first and second steps.

A total of 72 studies was included in this meta-analysis.[8] The literature search and the screening procedure are summarised in Fig. 1[9]

2.3. Study coding

Before coding, the two authors created a coding manual that provides guidelines on how to consistently extract information about effect sizes and moderator variables from the studies included in the sample. Comments and suggestions on this coding manual were given by a researcher in the area of education and technology. The revised version of the coding manual was then tested by comparing the codes generated by the two authors for 5 randomly selected studies. Following some minor modifications, the two authors, working independently, performed the coding on the remaining 67 studies. The Kappa value between them was 0.83, indicating relatively good consistency. However, when disagreement arose, the studies in question were re-examined by both authors together until a final agreement was reached.

2.3.1. Effect size calculations

In an attempt to compare the estimates of various ed-tech interventions on different academic outcomes, following the approach of similar earlier systematic reviews (e.g., Escueta et al., 2020) and meta-analyses (e.g., Ni, Cheung, & Shi, 2022), we used Cohen's *d*. Although results from different studies are never fully comparable, Cohen's *d* does offer valuable insights into the overall magnitude of impact across diverse programme contexts. Not only is Cohen's *d* the most widely employed effect size to measure the magnitude of group differences (McCoach & Siegle, 2009), but it is also the most used among the studies in our sample that report effect sizes. In those studies where Cohen's *d* values are not provided, it was possible to compute these using information therein contained. Cohen's *d* was calculated by dividing the mean difference in performance between treatment (exposure to ed-tech intervention) and control conditions (no exposure to ed-tech intervention) by the pooled standard deviation ($d = \frac{M_1 - M_2}{S_p}$; $S_p = \sqrt{\frac{(n_1-1)S_1^2 + (n_2-1)S_2^2}{(n_1-1)+(n_2-1)}}$, with M_1, M_2, S_p, n_1, n_2, S_1, S_2, denoting the means of the treatment group and control group, pooled standard deviation of both groups, the sample sizes of the treatment group and control group, and the standard deviation of the treatment group and control group). Additionally, if effect sizes are reported using Hedge's *g*, these were converted into Cohen's *d* statistics using the formula in Harrer, Cuijpers, Furukawa, and Ebert (2021) $\left(d = \frac{g}{1 - \left(\frac{3}{4(n_1+n_2-2)-1}\right)}\right)$. Finally, Cohen's *d* was calculated from pre-test post-test designs employing the formula in Morris (2008).

Cohen's *d* standard error is also missing in a number of studies. A few strategies have been employed to address this situation. For example, if information on sample sizes is available, Cohen's *d* standard error was calculated through the formula reported in Cooper and Hedges (1994). Where information on sample sizes is not included in the studies but exact *p*-values are instead reported, the formula provided by Higgins and Green (2011) was employed to calculate standard errors.

2.3.2. Moderator variables

For each effect size, we coded several moderator variables[10], that is, factors potentially influencing the size of the impact of ed-tech interventions on student achievement.

a) Type of publication

We distinguished between peer-reviewed journal articles and other studies. Publication type is a common moderator in meta-analysis. It is expected that peer-reviewed journal articles are of higher scientific rigour and less likely to include typos or errors in the reported results.

b) Publication year

Publication year is yet another typical moderator variable in meta-analysis. In our study, this factor may provide an indication about how the overall effectiveness of ed-tech applications has changed over time[11] (Cheung & Slavin, 2013). This is relevant because

[8] Information on the timing of the ed-tech intervention is missing in some of the selected studies (e.g., Verhallen & Bus, 2010). However, these studies take place in countries whose income classification by the WB has not changed over time (e.g., Netherlands has always been a high-income country). This means that the expression "at the time of the ed-tech intervention" in the eight inclusion and exclusion criterion (see Table 1) is redundant in these cases. Please note also that, although the title of the studies by Berlinski et al. (2021) and Berlinski et al. (2022) is the same, the latter is a revised version of the former and includes different estimates.

[9] As illustrated in Fig. 1, we were able to have access to the full text of all the studies identified in each step of the literature search.

[10] Information on all moderator variables was available for all the effect sizes included in our sample.

[11] Although the timing of the ed-tech interventions is the appropriate variable to look at in assessing how the overall effectiveness of these interventions has changed over time, as stated earlier, this information is missing in some of the studies included in our sample. The rationale for using year of publication is that it may be correlated with the timing of the ed-tech interventions.

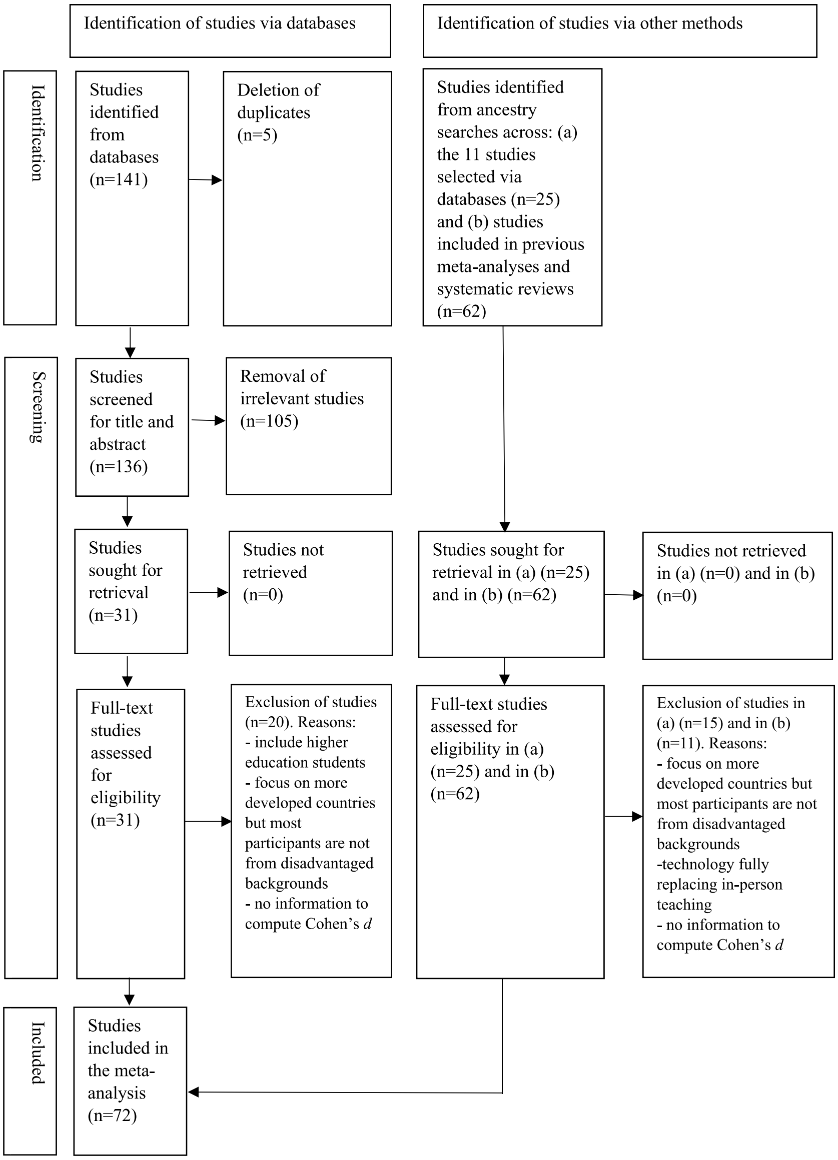

Fig. 1. Flowchart illustrating the review selection process.

one might expect that ed-tech interventions will become more effective as time goes on because of the continued and significant advances in technology.

c) Type of ed-tech intervention

Following Escueta et al. (2020), ed-tech interventions are classified into three categories: access to technology, computer-assisted learning (CAL), and behavioural interventions.[12] The first category comprises measures providing or facilitating the provision of computers/tablets/software and the internet to students. This type of intervention is common in rural areas and in less developed countries where many students lack the technology or internet access required for academic learning. For example, Cristia, Ibarraran, Cueto, Santiago, and Severin (2017) looked at the impact of a programme providing laptops to children in Peru, whereas Leuven, Lindahl, Oosterbeek, and Webbink (2007) analysed the effects of a computer subsidy in the Netherlands, designed for schools with a

[12] Four categories are included in the original classification developed by Escueta et al. (2020). However, the category of online courses cannot be considered in this work because studies evaluating interventions consisting of courses entirely delivered through the internet are excluded from our analysis (see inclusion and exclusion criteria).

large proportion of disadvantaged students.

The second category (CAL) comprises interventions utilizing technology to supplement traditional classroom instruction. Common examples of this category are educational software and applications to enhance math (e.g., Rutherford et al., 2014) and language (e.g., Macaruso, Hook, & McCabe, 2006) skills. However, CAL can also include more sophisticated tools like intelligent tutoring systems, educational games, virtual reality environments, or even software facilitating online tutoring programmes (e.g., Gortazar, Hupkau, & Roldán, 2022). Finally, one should note that CAL includes also Computer-Aided Instruction (CAI).

Behavioural interventions are defined as technology-mediated interventions designed to overcome or compensate for non-cognitive skill deficits that lead to negative student academic outcomes. They are often targeted at increasing parental involvement in their children's learning activities (e.g., programmes through which parents receive regular text messages containing tips on how to engage their children in reading activities).[13]

Previous review studies (e.g., Escueta et al., 2020) question the role of access to technology in positively affecting student academic achievement. On the other hand, they highlight the potential benefits associated with the other two types of interventions, especially CAL.

d) Level of education

In our analysis, we distinguished between primary (including kindergartens) and secondary education.[14] Earlier meta-analyses show mixed results about the role of educational level in explaining variations in the effects of ed-tech interventions on student performance. In their meta-analysis, Kazu and Kurtoğlu Yalçın (2022) show that there is no statistically significant difference in the impact of flipped classroom learning on student performance among studies focusing on elementary, secondary and postsecondary education. On the other hand, Ran, Kasli, and Secada (2021) observe that computer technology interventions have a larger effect for kindergarten and primary school students than for high school students. Digital tools can play a key role in enhancing the learning outcomes of students in the first stages of their education. They enable students to enjoy and have a positive attitude towards learning, promote engagement and contribute to the formation of problem-solving skills (Sun, Chen, & Ruokamo, 2021).

e) Subject area

Following the approach of several previous meta-analyses (e.g., Di Pietro, 2023), we grouped subjects into three different broad categories: math/science, humanities and a mix category. In addition to general math and science, the first category covers biology as well as various areas of math (e.g., algebra) and specific math functions (e.g., subtraction). There is also one study (Beg, Lucas, Halim, & Saif, 2022) using combined math and science test scores. As for the category of humanities, this comprises the subjects of language, foreign language, and social studies. Different aspects of language learning are considered (e.g., reading, word recognition). Finally, the mix category refers to tests combining different subjects belonging to the first two categories together (e.g., math + Chinese in Mo, Huang, et al., 2015), GPA or overall academic achievement.

The hypothesis of heterogeneous effects of ed-tech interventions by subject is supported by the findings of several studies. Bulman and Fairlie (2016) argue that it is easier to develop effective software packages for math than for language. In the meta-analysis by Chauhan (2017), technological applications are found to have a smaller impact on student learning in social studies compared to language, math, and science and technology. Zheng, Warschauer, Lin, and Chang (2016) conclude that, while the impact of one-to-one laptop programmes on academic achievement is positive across five different subject areas, the largest effect is found for science.

On the other hand, in their meta-analysis Major et al. (2021) find that in low- and middle-income countries technology-supported learning initiatives are equally important in enhancing student performance in math and literacy. Similar effects in math and literacy are also found by Kim, Gilbert, Yu, and Gale (2021).

f) Geographical location

As outlined in the inclusion and exclusion criteria, we selected studies examining students in less developed countries as well as studies on more developed countries where more disadvantaged students make up the whole sample or its majority. Based on the literature, it is unclear whether ed-tech interventions can be more effective for the former or latter group of students. On the one hand, one may argue that technology is especially beneficial in less developed countries where teachers are, on average, less prepared and more absent than those in more developed countries. Therefore, in the former countries, as stated by Banerjee, Cole, Duflo, and Linden (2007), computers can replace teachers with less motivation and training. A similar but more general argument is advanced by Bulman

[13] In studies examining the effect of access to technology programmes the untreated group consists of students who did not receive any computer/tablet/software, were not connected to the internet or were not financially incentivised to purchase educational technology (Leuven et al., 2007). In studies looking at the impact of technology-enabled behavioural interventions the control group is composed by individuals (e.g., parents, teachers) that were not exposed to the treatment. Finally, in studies assessing the effectiveness of CAL the control group is made up by students (classes/-schools) that did not use technology to supplement in- and out-of-class teaching.

[14] Although this is a broad categorization, one needs to consider that it is very difficult to distinguish between lower primary and upper primary education and between lower secondary and upper secondary education in a wide cross-national context. For example, in Tanzania junior secondary education ends at grade 11 (Seo, 2017), whereas in the US senior high school begins at grade 9.

and Fairlie (2016). They claim that in less developed countries ed-tech may make up for the lower quality of education. On the other hand, however, as suggested by DeWitt and Alias (2019), several issues may make it more difficult to implement ed-tech programmes in less developed countries, which in turn may undermine their effectiveness. First, these countries are more likely to experience irregular electrical supply and slow internet speeds. This, for instance, could reduce the potential benefits associated with the use of a learning software that can only be accessed online. Second, there is also the possibility that specific instructional materials delivered through technology or even some learning tools may turn out not to be suitable for the culture, customs and morale of a less developed country. For example, between 2005 and 2017 in Malaysia teachers strongly objected to the introduction of mobile phones for learning and teaching as they argued that their use would cause a lot of disciplinary problems. Third, in the literature it is often suggested that to be successful in enhancing student achievement, technology needs to be properly integrated into the teachers' instruction and curriculum (Rodriguez-Segura, 2022). However, this is less likely to occur in less developed countries where many teachers have not received training in the pedagogies for computers in education. Additionally, in these countries teachers may be especially reluctant to acquire these competencies as they perceive this change to be a threat to traditional teaching practices (Hinostroza, 2018).

g) Control/s

Finally, we coded a variable which equals one if the model from which the effect size is extracted includes one or more control variables, and zero otherwise. One would expect the presence of control variables to reduce the magnitude of the effect of ed-tech interventions on student achievement.

2.4. Sample characteristics

Table 2 presents the studies included in the dataset. For each study, we report information on the author(s), year of publication, country examined, number of the effect sizes collected and their mean value.

The dataset used for the meta-analysis includes 740 effect sizes from 72 studies published between 2004 and 2023. Each study included in our dataset contains a number of effect sizes that vary from 1 to 48. The studies cover a total of 26 countries. The largest source countries are India (168 effect sizes) and the US (144 effect sizes).

Appendix B reports the definition and the descriptive statistics of the variables used in our analysis. It also indicates the number of effect sizes for each moderator variable and the number of studies that include each moderator variable.

2.5. Risk of bias assessment

The risk of bias in each of the studies included in our sample was independently assessed by the two authors. Inter-rater reliability reported by Cohen's Kappa was rather high (0.78), but any disagreement was resolved through discussions. While the Risk Of Bias in Non-randomised Studies of Interventions (ROBINS-I) (Sterne et al., 2016) was used to evaluate studies with a quasi-experimental design, Version 2 of the Cochrane Risk of Bias tool for randomised trials (RoB 2) (Sterne et al., 2019) was employed to assess the other studies. As shown in Appendix C, a rather common issue with the latter group of studies lies in limited information on, or problems with, the randomisation process. An additional issue is the use of an unreliable measure for student achievement. As regard studies using quasi-experimental approaches, as reported in Appendix D, sample selection issues and missing data problems (e.g., no outcome data for some members of the control (treated) group) are the most common sources of potential bias.

2.6. Models and estimators

2.6.1. Model to compute summary effect size estimates

The fixed effects (FE) and random effects (RE) models are two approaches frequently employed in meta-analysis. They are based on different assumptions. The FE model assumes that there is one true effect size common to all studies and that all differences in the observed effects can be ascribed to within-study sampling error. In contrast to this, the RE model assumes that the effect size may vary between studies not only as a result of the within-study sampling error, but also because there is heterogeneity in true effects between studies. This additional variability is typically modelled using a between-study variance parameter (often called τ^2). Considering the different characteristics of the studies included in our sample, it is difficult to assume that there is a common true effect shared by all studies. Thus, it is anticipated that the RE model would be more appropriate, i.e., estimating the mean of the distribution of true effects. Specifically, in line with the approach of Kaiser and Menkhoff (2020), we estimate the mean of the distribution of true effects using a RE meta-analysis based on a Robust Variance Estimation (RVE) developed by Tanner-Smith and Tipton (2014). The RVE approach enables to account for the possibility that multiple effect sizes from the same study are correlated between each other. The advantages of this method are that there is no need to eliminate any effect size (to ensure their statistical independency) and no information is needed on the intercorrelation between effect sizes within studies.

2.6.2. Methods to test and correct for publication bias

There are two factors suggesting a potential bias towards positive results. First, manuscripts finding statistically significant positive findings are more attractive to researchers, referees and editors (Begg & Belin, 1988). Second, companies significantly investing in ed-tech products and services may also welcome research results suggesting a positive effect of technology on student learning (Escueta & Holloway, 2019).

Table 2
Sources for meta-analysis.

Authors	Year of publication	Country	Number of effect sizes collected	Mean effect size
Abrami et al.	2016	Kenya	3	0.38
Amendum et al.	2011	US	7	0.49
Aunio & Mononen	2018	Finland	9	−0.17
Bai et al.	2016	China	6	0.05
Bai et al.	2023	China	4	0.18
Baker et al.	2017	US	6	−0.01
Bando et al.	2017	Honduras	6	−0.06
Banerjee et al.	2007	India	13	0.21
Barrow et al.	2009	US	8	0.2
Beg et al.	2022	Pakistan	18	0.06
Bergman	2021	US	12	0.12
Bergman & Chan	2021	US	14	0.03
Bergman & Rogers	2016	US	4	0.06
Berlinski et al.	2022	Chile	5	0.09
Berlinski et al.	2021	Chile	1	0.08
Beuermann et al.	2015	Peru	2	0.07
Bianchi et al.	2022	China	4	0.19
Blimpo et al.	2020	Gambia	6	0.51
Borzekowski	2018	Tanzania	7	0.13
Borzekowski et al.	2019	India	48	0.16
Brown et al.	2020	Sudan	2	0.95
Büchel et al.	2022	El Salvador	6	0.28
Cardim et al.	2023	Angola	3	0.02
Carrillo et al.	2010	Ecuador	30	0.12
Chambers et al.	2006	US	10	0.14
Chambers et al.	2008	US	10	0.44
Cilliers et al.	2022	South Africa	9	0.05
Cristia et al.	2017	Peru	24	0.02
de Hoop et al.	2023	Zambia	21	0.25
Derksen et al.	2020	Malawi	6	0.02
Duflo et al.	2012	India	12	0.16
Gortazar et al.	2022	Spain	10	0.38
Ibe & Abamuche	2019	Nigeria	1	0.97
Ito et al.	2021	Cambodia	6	0.69
Johnston & Ksoll	2022	Ghana	29	0.16
Kraft & Monti-Nussbaum	2017	US	20	0.11
Kumar & Mehra	2018	India	1	0.16
Lai et al.	2015	China	4	0.1
Lai et al.	2016	China	8	0.14
Lai et al.	2013	China	6	0.12
Lehrer et al.	2019	Senegal	21	0.24
Leuven et al.	2007	Netherlands	18	−0.04
Linden	2008	India	26	−0.1
Linebarger et al.	2010	US	8	0.29
Lysenko et al.	2019	Kenya	15	0.58
Macaruso et al.	2006	US	4	0.96
Malamud et al.	2019	Peru	6	0.01
McManis & McManis	2016	US	2	0.38
Miller & Robertson	2011	Scotland	1	0.09
Mo et al.	2020	China	4	0.06
Mo et al.	2015(a)	China	24	0.12
Mo et al.	2013	China	4	0.06
Mo et al.	2014	China	6	0.18
Mo et al.	2015(b)	China	8	0.19
Muralidharan et al.	2019	India	29	0.26
Naik et al.	2020	India	36	0.13
Ntaila & Mbaraka	2023	Malawi	2	2.18
Piper et al.	2016	Kenya	6	0.26
Pitchford	2015	Malawi	13	0.41
Riley	2018	Uganda	16	0.05
Rouse & Krueger	2004	US	13	0.15
Rutherford et al.	2014	US	17	0.08
Santana et al.	2019	Chile	7	0.42
Schacter & Jo	2016	US	1	1.09
Schacter et al.	2016	US	1	0.57
Seo	2017	Tanzania	24	0.02
Setren	2023	US	4	0.12
Silander et al.	2016	US	3	0.12

(*continued on next page*)

Table 2 (*continued*)

Authors	Year of publication	Country	Number of effect sizes collected	Mean effect size
Verhallen & Bus	2010	Netherlands	8	0.94
Wennersten et al.	2015	India	3	0.71
Wolf et al.	2019	Ghana	2	−0.03
Yang et al.	2013	China	7	0.13

We employed the Doi plot to visually assess publication bias. Its use has two main advantages. First, it aids visualization of asymmetry (no asymmetry is observed in the absence of publication bias). Second, it quantifies the asymmetry using the Luis-Furuya-Kanamori (LFK) index. LFK index values within ±1 suggest no asymmetry, LFK index values exceeding ±1 but within ±2 indicate minor asymmetry, while LFK index values exceeding ±2 denote major asymmetry (Furuya-Kanamori, Barendregt, & Doi, 2018).

If evidence of publication bias is detected, several methods can be used to quantify its extent and correct for it. The most common is known as FAT (Funnel-Asymmetry Test)-PET (Precision-Effect Testing), initially proposed by Egger, Davey Smith, Schneider, and Minder (1997). The intuition behind it is that results of small studies may be a potential source of bias. Researchers willing to overestimate the effect of interest are more likely to select small positive studies than small negative studies. Given that small studies have greater variance in their results, in the presence of publication bias one can expect estimates and their standard errors to be correlated. The FAT-PET test involves estimating the following equation:

$$\beta_{ij} = \alpha_0 + \alpha_1 \left(SE_{ij}\right) + \varepsilon_{ij} \tag{1}$$

where β_{ij} is the i-th effect size collected in study j and SE_{ij} is the standard error of this effect size. However, Eq. (1) has two main problems. First, the error term is heteroskedastic. To deal with this problem, one can divide each side of Eq. (1) by SE_{ij}. Thus, we obtain:

$$t_{ij} = \alpha_1 + \alpha_0 \left(1 / SE_{ij}\right) + \omega_{ij} \tag{2}$$

where t_{ij} is the *t*-statistic of the i-th effect size collected in study j. The second problem lies in the correlation between effect sizes from the same study. Such an issue is addressed by clustering standard errors at the study level. In Eq. (2), while α_1 captures the extent of publication bias, α_0 measures the mean effect beyond bias.

Additionally, following the approach of Zigraiova, Havranek, Irsova, and Novak (2021), Eq. (2) can be estimated using as weights both the inverse of the variance and the inverse of the number of effect sizes reported in each study. The purpose of the inverse variance weight is to give greater importance to more precise effect sizes. The second weight is used in order to assign the same importance to each study regardless of the number of effect sizes included.

Stanley and Doucouliagos (2012) and Stanley and Doucouliagos (2014) propose a quadratic version of the FAT-PET, the so-called PEESE (Precision-Effect Estimate with Standard Error). Hence, the following equation can be estimated:

$$t_{ij} = \alpha_1 SE_{ij} + \alpha_0 \left(1 / SE_{ij}\right) + \mu_{ij} \tag{3}$$

Finally, three additional techniques can be employed in an attempt to correct for publication bias. First, the Top 10% approach consists in computing an average weighted impact for the most precise (smallest standard errors) 10% of the reported estimates. This is because one would expect the most precise estimates to be less likely to be subject to selection for statistical significance (Stanley, Jarrell, & Doucouliagos, 2010). Second, an average weighted impact for the adequately powered (WAAP) estimates (Ioannidis, Stanley, & Doucouliagos, 2017) can be calculated (Kroupova, Havranek, & Irsova, 2024). Only effect sizes with power above 80% are considered. An effect size has 80% or higher power if its standard error is less than the absolute value of the true effect divided by 2.8. Third, one can use the trim-and-fill method (Duval & Tweedie, 2000). It is a parametric technique based on the evaluation of the funnel plot asymmetry. The potentially missing effect sizes because of publication bias are estimated, and then a bias-adjusted overall effect size is provided (Chang et al., 2022).

2.6.3. Estimators for the meta-regression equation

In order to investigate potential sources of heterogeneity in effect sizes, the following meta-regression equation is estimated:

$$\beta_{ij} = \alpha_0 + \alpha_1 \left(SE_{ij}\right) + \sum_{k=1}^{10} \alpha_k X_{k,ij} + \varphi_{ij} \tag{4}$$

where $X_{k,ij}$ represents the set of moderator variables described in Section 2.3.2. The subscript i stands for the number of effect sizes included in the sample, the subscript j refers to the number of studies, and the subscript k represents the number of moderator variables. α_1 captures the severity of publication bias conditional on the inclusion of moderator variables.

Eq. (4) is estimated using weighted least squares (WLS) with weights equal to the inverse of each effect size's variance. This method allows us to account for heteroscedasticity. Additionally, as argued by Stanley and Doucouliagos (2015), WLS is found to outperform conventional meta-regression techniques (e.g., RE meta-regressions) in presence of publication bias. To account for the potential dependence of multiple estimates from the same paper, standard errors are clustered at the study level. This is in line with the approach followed by earlier meta-analyses (e.g., Popp, 2023).

A considerable problem in estimating Eq. (4) lies in the selection of the moderator variables to be included in the model. There is the risk that the inclusion of all potentially relevant explanatory variables may inflate standard errors, leading to inefficient estimates (Di Pietro, 2023). Hence, following several meta-analyses (e.g., Anderson, Jalles D'Orey, Duvendack, & Esposito, 2017; de Linde Leonard, Stanley, & Doucouliagos, 2014; Ugur, Churchill, & Luong, 2020), we used a general-to-specific modelling approach and a weighted average least squares (WALS) procedure[15] to deal with model uncertainty. The former consists in sequentially removing the variables with the largest *p*-values, until all remaining variables are statistically significant at the 5% level. WALS combines idea from Bayesian and frequentist approaches to model averaging (Magnus, Powell, & Prufer, 2010). In WALS, the impact of a moderator variable is considered not to be weak if its *t*-statistic is greater than one in absolute value.

3. Results

Our results are presented in three steps: first, estimated summary effect sizes are reported (Section 3.1.); second, the possibility of publication bias is analysed (Section 3.2.); and third, potential sources of heterogeneity of results are investigated (Section 3.3.).

3.1. Summary effect size estimates

Table 3 reports the results from an intercept-only random effect RVE model.[16] In this model, one can interpret the intercept as the precision-weighted mean effect size adjusted for effect-size dependence (Friese, Frankenbach, Job, & Loschelder, 2017). Our findings show that, compared to control group students, more disadvantaged students receiving an educational technology intervention show greater academic performance. Specifically, as depicted in Column (1) of Table 3, we find an average weighted impact estimate of 0.202 standard deviations (SE = 0.029, *p*-value = 0.000, 95% CI [0.145, 0.259]).[17]

Results from Table 3 confirm the appropriateness of the RE model. The estimated τ^2 is different from zero, suggesting that there is significant true variability among the effect sizes.

The average weighted impact estimate for students in less developed countries is 0.233 standard deviations (Column (2) of Table 3), whereas the corresponding figure for more disadvantaged students in more developed countries is 0.178 standard deviations (Column (3) of Table 3). Post-hoc analysis shows that these two summary effect sizes are not statistically different from each other.[18] In Section 3.3., we test whether this result holds also in the meta-regression analysis.

3.2. Publication bias

Before testing for publication bias using the LFK index, a funnel plot is presented in Fig. 2. In the absence of publication bias, effect sizes are expected to be symmetrically distributed around the overall mean effect size. However, this figure shows a clearly asymmetrical shape, with most effect sizes with high standard errors indicating a performance-enhancing effect of technology.

As shown in Fig. 3, the Doi plot confirms the existence of publication bias as a major asymmetry is detected[19] (LFK index = 4.05)[20].

Results from the FAT-PET model, which are shown in Panel A of Table 4, show evidence of strong publication bias towards studies reporting positive effects of ed-tech interventions on student achievement.[21] After accounting for publication bias, the mean effect size is still positive and statistically significant, though its magnitude is smaller than the one reported in Section 3.1. As depicted in Panel B of Table 4, PEESE results are also in line with the claim that publication bias is robustly positive, but this bias does not invalidate the positive effect of ed-tech interventions on student achievement.

The findings from Top10%, WAAP and trim-and-fill,[22] which are reported in Panel C of Table 4, confirm the positive, but smaller, effect of ed-tech interventions, after controlling for publication bias.

[15] WALS is implemented using the Stata command *wals* developed by De Luca and Magnus (2011). We treated all moderator variables as auxiliary covariates while the constant is treated as a focused regressor.

[16] We used the *robumeta* package in Stata to estimate RVE models. The average correlation between all pairs of effect sizes within studies ($\hat{\rho}$) is assumed to be 0.8.

[17] We used all effect sizes included in our sample to compute the results displayed in Column (1) of Table 3. However, to test the sensitivity of these findings, we have also replicated this analysis excluding outliers. In line with the approach followed by several studies (see, for instance, Fodor et al., 2018), we define outliers as effect sizes whose 95% confidence interval is outside the 95% confidence interval of the pooled effect size. Compared to estimates shown in Column (1) of Table 3, the removal of the outliers (189 effect sizes) makes the overall effect size smaller (0.156) and the 95% confidence interval narrower [0.137, 0.183]. By contrast, and in line with expectations, the average weighted impact estimate is larger (0.233) if only peer-reviewed journal articles are considered in the sample.

[18] We estimated a random effect RVE model where the effect size is regressed against the dummy variable for more disadvantaged students in more developed countries in addition to a constant (the Stata command *robumeta* is used). The coefficient on this dummy is expected to capture the difference in the average weighted impact estimate between more disadvantaged students in more developed countries and students in less developed countries (base category). This estimated coefficient turns out not to be statistically different from zero (results are available upon request).

[19] We used the *lfk* command in Stata to generate the Doi plot and estimate the LFK index.

[20] A major asymmetry is also detected if one separately analyses publication bias in studies on students in less developed countries and those on more disadvantaged students in more developed countries.

[21] A similar result (available upon request) is found using the *meta bias, egger* command in Stata.

[22] The Stata command *meta trimfill* has been used.

Table 3
Results of estimating unconditional meta-regression models with robust variance estimation.

	Dependent variable: Academic achievement for students in less developed countries or for more disadvantaged students in more developed countries (Cohen's *d*) (1)	Dependent variable: Academic achievement for students in less developed countries (Cohen's *d*) (2)	Dependent variable: Academic achievement for more disadvantaged students in more developed countries (Cohen's *d*) (3)
Constant	0.202***	0.233***	0.178***
(Standard Error)	(0.029)	(0.053)	(0.029)
N. effect sizes	740	447	293
N. studies	72	34	38
τ^2	0.035	0.048	0.028
95% confidence interval	0.145 - 0.259	0.125 - 0.341	0.118–0.238

*, **, and *** denote statistical significance at 10, 5, and 1%, respectively.

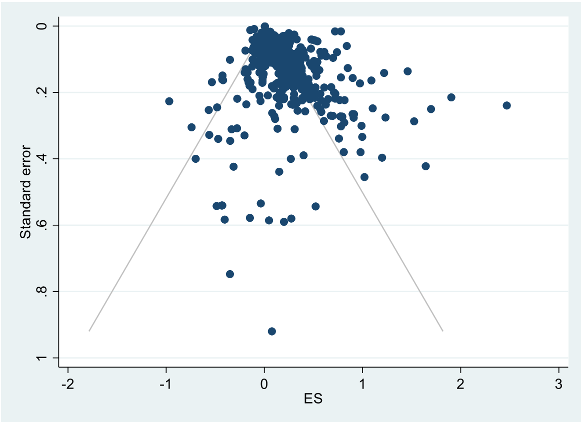

Fig. 2. Funnel plot.

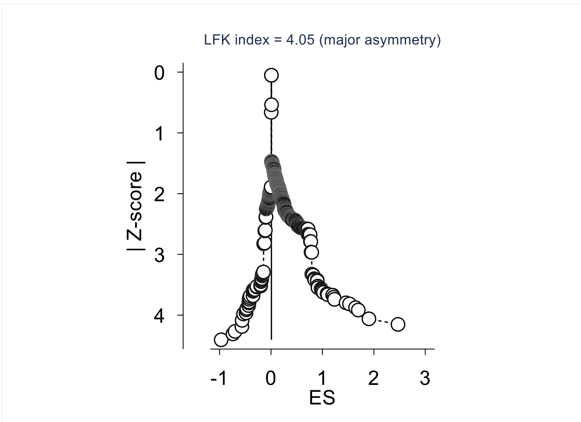

Fig. 3. Doi plot.

3.3. Heterogeneity

Table 5 reports the results of our meta-regression model. Column (1) of Table 5 shows the estimates from Eq. (4) where all our moderator variables are included. However, as reported in Column (2) of Table 5, five variables are dropped from the meta-regression

Table 4
Linear and nonlinear techniques to detect publication bias.

Panel A: FAT-PET	
Mean beyond bias	0.006***
(1/SE)	(0.001)
Publication bias	1.753***
(Constant)	(0.228)
N. Observations	740
Panel B: PEESE	
Mean beyond bias	0.014***
(1/SE)	(0.005)
Publication bias	7.137***
(SE)	(1.813)
N. Observations	740
Panel C: Top 10%, WAAP and Trim-and-fill	
Top 10%	
Mean beyond bias	0.085**
	(0.023)
N. Observations	74
WAAP	
Mean beyond bias	0.098***
	(0.014)
N. Observations	334
Trim-and-fill	
Bias-adjusted overall effect size	0.081***
	(0.005)
N. Imputed Observations	159

In Panels A, B and C (Top 10% and WAAP) the regression uses standard errors clustered at study level. It is also estimated employing weighted least squares and using as weights both the inverse variance and the inverse of the number of estimates reported per study. As regards trim-and-fill, the DerSimonian–Laird method is used. *, **, and *** denote statistical significance at 10, 5, and 1%, respectively.

when applying the general-to-specific approach. Interestingly, our moderator variable capturing students' geographical location is not included in this specification. Hence, consistent with the results of Table 3, this finding would seem not to support the hypothesis of a significant difference in the impact of ed-tech interventions between students in less developed countries and more disadvantaged students in more developed countries.

Our estimates suggest that CAL and technology-enabled behavioural interventions are more effective in raising the achievement of less advantaged students than access to technology interventions (0.116 SD and 0.094 SD, respectively[23]). Additionally, a larger impact of ed-tech interventions on the performance of less advantaged students is found in studies published in peer-reviewed journals relative to other types of studies. Ed-tech interventions have also a slightly more positive effect on student achievement in math and science than humanities. The coefficient on year of publication has a positive sign and is statistically significant, suggesting that recent studies tend to report a larger effect on student achievement than older publications.

Next, in our reduced specification we replace the nominal year of publication with the year in which the first draft of the study appeared in Google Scholar. The rationale for this is that articles are subject to different publication lags depending on the journal in which they have been accepted for publication (Di Pietro, 2022; Zigraiova et al., 2021). Yet, as shown in Column (3) of Table 5, the results are largely unchanged.

The WALS results, which are reported the first half of Table 6, identify two more relevant explanatory factors in addition to those already selected through the general-to-specific approach.[24] However, a "frequentist check" of the WALS estimation, where the effect size is regressed against all the moderator variables with a *t*-statistic greater than one in absolute value, shows that these two additional regressors are not statistically significant at conventional levels. Furthermore, in contrast to the results depicted in Table 5, estimates shown in the second half of Table 6 suggest that year of publication does not explain variation in the reported estimates.

4. Conclusions, discussion and implications

This paper adds to the existing literature by performing a meta-analysis that examines the effect of digital technologies on learning

[23] The achievement-enhancing effect of CAL is found not to be statistically different from that of behavioural interventions.

[24] We also employed a Bayesian Model Averaging (BMA) approach to tackle model uncertainty. Results (available upon request) are very similar to those using WALS.

Table 5
Meta-regression results.

	WLS General (1)	WLS Specific (2)	WLS (with Google Scholar year replacing Year of Publication) Specific (3)
Constant	−9.387	−6.413**	−6.928**
	(6.786)	(2.511)	(2.807)
Standard Error	2.141***	2.245***	2.243***
	(0.439)	(0.270)	(0.270)
Year of publication	0.005	0.003**	
	(0.003)	(0.001)	
Google Scholar year			0.003**
			(0.001)
Control/s	−0.087		
	(0.072)		
Subject area (Base category: Humanities)			
Math/Science	0.011***	0.011***	0.011***
	(0.003)	(0.002)	(0.002)
Mix	0.021		
	(0.024)		
Level of education (Base category: Primary)			
Primary and Secondary	0.077		
	(0.056)		
Secondary	−0.017		
	(0.030)		
Type of ed-tech intervention (Base category: Access to technology)			
CAL	0.149***	0.116***	0.110***
	(0.030)	(0.018)	(0.018)
Behavioural interventions	0.151***	0.094***	0.090***
	(0.047)	(0.024)	(0.023)
Geographical location (Base category: Students in less developed countries)			
More disadvantaged students in more developed countries	−0.052*		
	(0.030)		
Type of publication (Base category: Other publications)			
Peer-reviewed journal articles	0.107***	0.058***	0.060***
	(0.044)	(0.021)	(0.021)
R-squared	0.295	0.262	0.262
N. Observations	740	740	740

Note. The dependent variable in all regressions is the effect size. Standard errors are reported in parentheses.
All regressions use standard errors clustered at study level to adjust for data dependence.
All regressions are estimated using weighted least squares with inverse variance weighting.
*, **, and *** denote statistical significance at 10, 5, and 1%, respectively.

Table 6
WALS and frequentist check.

	WALS			Frequentist check		
	Coef.	St. Error	*t*-stat	Coef.	St. Error	*p*-value
Year of publication	0.031	0.023	**1.33**	0.00	0.00	0.22
Control/s	−0.069	0.015	**−4.72**	−0.09	0.07	0.20
Standard Error	−60.05	46.53	**−1.29**	2.27	0.28	0.00
Math/Science	0.010	0.004	**2.43**	0.01	0.00	0.00
Mix	0.012	0.018	0.66			
Primary and Secondary	0.086	0.135	0.64			
Secondary	−0.010	0.015	−0.63			
CAL	0.141	0.023	**6.11**	0.14	0.03	0.00
Behavioural interventions	0.157	0.032	**4.84**	0.15	0.05	0.00
More disadvantaged students in more developed countries	−0.058	0.017	**−3.48**	−0.04	0.04	0.23
Peer-reviewed journal articles	0.095	0.023	**4.14**	0.10	0.04	0.02
N. Observations	740			740		

The frequentist check comprises variables that turn out to have a *t*-stat greater than 1 in absolute value, according to WALS. Standard errors in the frequentist check are clustered at the study level. Both regressions are weighted by the inverse variance.

outcomes, focusing on less advantaged students. A novelty is that we use a broad definition that includes all students in less developed countries as well as more disadvantaged students in more developed countries. While in less developed countries digital technologies may help to address issues such as low supply of qualified teachers and poor quality educational materials, in more developed countries they can play an important role too, for instance, by boosting students' motivation and engagement, and enhancing the quality of education for students from rural areas.

We consider only studies presenting evidence from experimental or quasi-experimental research designs. Our sample comprises 740 effect sizes from 72 papers.

Our results indicate an overall modest but positive and statistically significant effect of technology on the achievement of less advantaged students. This effect, though smaller, remains even after selective reporting favouring beneficial outcomes is accounted for. Specifically, after controlling for publication bias, the relevant effect size is at best about 0.1 standard deviations.

The estimates of our multivariate meta-regression analysis show that CAL and technology-enabled behavioural interventions lead to greater achievements than access to technology interventions. Interestingly, the former types of interventions seem to be equally important in improving student performance. While the potential role of CAL programmes in supporting student achievement is quite well-known (Escueta et al., 2020), our results would seem to suggest that behavioural interventions work especially well in environments characterized by low levels of cultural capital and poor educational aspirations. As in our sample most of the interventions falling under this category aim at increasing parental information and engagement via SMS messages, the meta-regression results emphasize the importance of family and community involvement for more disadvantaged students (Heers, Van Klaveren, Groot, & Maassen van den Brink, 2016) and show that technology interventions can make a relevant contribution in this regard (Goodall, 2016).

Additionally, insights from individual studies seem to indicate that pro-active text messages are more effective than informational text messages. While the latter provide information on children's performance, attendance or behaviour at school, the former indicate concrete actions that parents can do to support their children's learning. For example, in Santana, Monti-Nussbaum, Carmona, and Claro (2019) parents were encouraged to complete short and simple weekly activities with their children, whereas in Kraft and Monti-Nussbaum (2017) suggestions for specific literacy development techniques were offered to parents. This conclusion is consistent with the idea that, to increase parent motivation, tailored goal setting messages work better than basic impersonalised messages (Heppen, Kurki, & Brown, 2020).

Our meta-regression estimates show also that the achievement-enhancing effects of ed-tech programmes on students in less developed countries are not statistically different from those on more disadvantaged students in more developed countries. While these programmes may have a higher potential to boost student performance in less developed countries, our result perhaps reflects difficulties in their implementation (e.g., irregular electric supply, unstable or low-speed internet connection, low level of teachers' digital skills) (Aung & Khaing, 2015; Eltahir, 2019). However, it is important to note that the effect of higher academic ability on labour market outcomes tends to be higher for students in less developed countries than for those in more developed countries. Available evidence would in fact seem to suggest that the same increase in student achievement is expected to deliver higher financial returns for students in less developed countries than for those in more developed countries. In several African countries an increase in math test scores of 0.1 standard deviations is found to lead to an increase in income of between 2% and 6.5% (Dickerson, McIntosh, & Valente, 2015), whereas Chetty, Friedman, and Rockoff (2014) conclude that in the US increasing student achievement by 0.1 standard deviations translates, on average, into a 1.3% increase in annual lifetime earnings.

Larger impacts of ed-tech programmes tend to be reported in peer-reviewed journals than in other types of publication. Additionally, ed-tech initiatives yield slightly greater improvements in student achievement in math and science than in humanities. Nevertheless, evidence from individual studies suggests that the impact of different interventions may vary significantly across contexts and student populations. This underscores the importance of adapting ed-tech interventions to specific needs. For instance, computer assisted language learning programmes seem to be particularly effective for less advantaged students in more developed countries, especially in high migration contexts where language barriers are likely to be a problem (e.g., Chambers et al., 2008; Macaruso et al., 2006; Verhallen & Bus, 2010).

Overall, our results suggest that more needs be done to unleash the full potential of technology in boosting the achievement of less advantaged students. As for access to technology programmes, it is possible that many less advantaged students are not aware of the contribution that technology can play in assisting learning. Cross-national evidence shows that these students are less likely to use technology for academics compared to their more advantaged peers (OECD, 2016). Similarly, data from the US indicate that while students from lower-income families are more likely to use computers for repetitive practice, those from higher-income families tend to use computers more often for more sophisticated, intellectually complex applications (Becker, 2000). The provision of technology needs therefore to be accompanied by proper guidance and supervision to ensure that all students can harness the benefits of technology to improve their educational performance.

As far as CAL is concerned, the lower level of digital competence of less advantaged students may make them less likely to fully take advantage of the learning opportunities offered by technology. On the one hand, several studies (e.g., van de Werfhorst, Kessenich, & Geven, 2022) highlight the large digital skill gap between more advantaged and less advantaged students. On the other hand, it is often suggested how advanced digital skills are increasingly critical for students to be able to benefit from the performance-enhancing effects of technology (Kure, Brevik, & Blikstad-Balas, 2023). A lot of tasks can be performed using digital learning programmes, but the more complex ones often require advanced digital skills. Hence, it is of crucial importance that more training is provided by schools to students who are digital illiterate or have only basic digital skills.

In low socio-economic contexts, technology-enabled behavioural interventions may need to be accompanied by other measures in order to be more effective. For example, interventions aimed at increasing parental involvement in education may work better if they are complemented by programmes providing content and in-person support. While behavioural interventions are designed to overcome psychological and informational barriers, these other programmes are expected to have an impact on student cognitive skills.

Given the effectiveness of both CAL and technology-enabled behavioural interventions in raising the achievement of less advantaged students, a practical implication of our findings is to combine these two types of intervention into a single ed-tech programme. In this way, one can maximise the benefits, potentially leading to synergistic outcomes. Furthermore, given the low cost of implementation of behavioural interventions, such a combination may turn out to be a promising cost-effective approach for using technologies to reduce educational inequalities.

5. Limitations and future directions

This article has three limitations that may have implications for future research. First, we were unable to differentiate between lower and upper primary or secondary education because of the challenges of conducting this analysis in a wide transnational context. Future research could look at these distinctions focusing on a group of more homogeneous countries (e.g., the EU). Second, while we have not considered the impact of technology on digital literacy, there is evidence suggesting a potential link between the two, even when the intervention is limited to technology provision (e.g., Beuermann, Cristia, Cueto, Malamud, & Cruz-Aguayo, 2015; Malamud, Cueto, Cristia, & Beuermann, 2019). Third, we acknowledge that educational technology is a fast-evolving area and some of our findings may possibly change in the future due to an increase in the number of studies examining the effect of emerging technologies on the achievement of less advantaged students. For instance, the study by García-Vandewalle García, García-Carmona, Trujillo Torres, and Moya-Fernández (2022), which relies on the views of eight international experts in education, concludes that new technologies can play an important role in improving the achievement of students in disadvantaged contexts.

CRediT authorship contribution statement

Giorgio Di Pietro: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jonatan Castaño Muñoz:** Writing – review & editing, Methodology, Investigation, Data curation, Conceptualization.

Declarations of competing interest

None.

Appendix A. *Search terms*

Category	Keywords
Setting of interest	primary (OR education OR student OR school) OR elementary (OR education OR student OR school) OR secondary (OR education OR student OR school) OR preschool OR kindergarten OR middle (school OR student) AND
Exposure	computer OR mobile OR laptop OR tablet OR software OR internet OR apps (OR applications) OR digital OR virtual OR technolog* OR text messages OR SMS AND
Methodology	experimental OR quasi-experimental OR instrumental OR regression discontinuity OR randomized control trial OR randomised control trial OR RCT OR propensity score OR difference-in-difference* AND
Outcome	student (OR academic OR scholastic) performance (OR achievement OR learning OR outcome) OR (pupil (OR academic OR scholastic) performance (OR achievement OR learning OR outcome) OR test score OR learning ability AND
Socio-economic condition	less developed countr* OR developing countr* OR underdeveloped countr* OR under-developed countr* OR low* GDP countr* OR low* socio-economic (OR socioeconomic) OR disadvantaged OR less advantaged OR less privileged OR unprivileged OR vulnerable OR less affluent OR less wealthy OR minority OR low*-income OR poor* income OR migrant OR rural OR remote

Appendix B. Definition and descriptive statistics

Variable name	Variable description	Unweighted Mean (Standard deviation) (1)	Weighted (by the inverse of the number of estimates reported in each study) Mean (Standard deviation) (2)	Number of effect sizes/ number of studies including each moderator variable (3)
Effect size	Estimated effect size (Cohen's *d*)	0.177 (0.288)	0.260 (0.394)	740/72
Effect size's standard error	Estimated standard error of Cohen's *d*	0.114 (0.099)	0.125 (0.102)	740/72
Year of publication	Year of publication of the study where the effect size is extracted	2016.197 (4.916)	2016.386 (4.755)	740/72

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Variable name	Variable description	Unweighted Mean (Standard deviation) (1)	Weighted (by the inverse of the number of estimates reported in each study) Mean (Standard deviation) (2)	Number of effect sizes/ number of studies including each moderator variable (3)
Control/s	Dummy, 1 if the model from which the effect size is extracted includes one or more control variables, 0 otherwise	0.696 (0.460)	0.592 (0.492)	515/52
Subject area				
Math/Science	Dummy, 1 if the subject area is math or science, 0 otherwise	0.451 (0.498)	0.501 (0.500)	334/56
Humanities (base category)	Dummy, 1 if the subject area is humanities, 0 otherwise	0.423 (0.494)	0.406 (0.491)	313/51
Mix	Dummy, 1 if student achievement in different subject areas is considered, 0 otherwise	0.126 (0.332)	0.093 (0.290)	93/16
Level of education				
Primary (base category)	Dummy, 1 if the education level is primary school (or kindergarten), 0 otherwise	0.727 (0.446)	0.752 (0.432)	538/54
Secondary	Dummy, 1 if the education level is secondary school, 0 otherwise	0.250 (0.433)	0.221 (0.415)	185/16
Primary and Secondary	Dummy, 1 if the education level is both primary and secondary school, 0 otherwise	0.023 (0.150)	0.028 (0.164)	17/2
Type of ed-tech intervention				
CAL	Dummy, 1 if the ed-tech intervention is a computer-assisted learning programme, 0 otherwise	0.757 (0.429)	0.742 (0.438)	560/54
Behavioural interventions	Dummy, 1 if the ed-tech intervention is behavioural in nature, 0 otherwise	0.138 (0.345)	0.152 (0.359)	102/11
Access to technology (base category)	Dummy, 1 if the ed-tech intervention provides students with access to technology and/or the internet, 0 otherwise	0.105 (0.307)	0.107 (0.309)	78/10
Geographical location				
Students in less developed countries (base category)	Dummy, 1 if the effect size is extracted from a study examining students in less developed countries, 0 otherwise	0.604 (0.489)	0.476 (0.500)	447/34
More disadvantaged students in more developed countries	Dummy, 1 if the effect size is extracted from a study examining more disadvantaged students in more developed countries, 0 otherwise	0.396 (0.489)	0.524 (0.500)	293/38
Type of publication				
Peer-reviewed journal articles	Dummy, 1 if the effect size is extracted from a peer-reviewed journal article, 0 otherwise	0.788 (0.409)	0.807 (0.395)	583/58
Other publications (base category)	Dummy, 1 if the effect size is extracted from a publication that is not a peer-reviewed journal article, 0 otherwise	0.212 (0.409)	0.193 (0.396)	157/14

Appendix C. Quality assessment for RCTs (RoB 2)

Study	Risk of bias arising from the randomisation process	Risk of bias due to deviations from the intended intervention	Missing outcome data	Risk of bias in the measurement of the outcome	Risk of bias in the selection of the reported results	Overall risk of bias
Abrami, Wade, Lysenko, Marsh, and Gioko (2016)	High	Low	Some concerns	Low	Low	High
Amendum, Vernon-Feagans, and Ginsberg (2011)	Some concerns	Low	Low	Some concerns	Low	Some concerns
Aunio and Mononen (2018)	High	Low	Low	Low	Low	High
Bai, Mo, Zhang, Boswell, and Rozelle (2016)	Low	Low	Low	Low	Low	Low
Bai et al. (2023)	Some concerns	Low	Low	Low	Low	Some concerns
Baker et al. (2017)	Some concerns	Low	Some concerns	Low	Low	Some concerns
Bando, Gallego, Gertler, and Romero Fonseca (2017)	Some concerns	Low	Low	Low	Low	Some concerns

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Study	Risk of bias arising from the randomisation process	Risk of bias due to deviations from the intended intervention	Missing outcome data	Risk of bias in the measurement of the outcome	Risk of bias in the selection of the reported results	Overall risk of bias
Banerjee et al. (2007)	Low	Low	Low	Low	Low	Low
Barrow et al. (2009)	Low	Some concerns	Low	Low	Low	Some concerns
Beg et al. (2022)	Some concerns	Low	Low	Low	Low	Some concerns
Bergman (2021)	Low	Low	Low	Low	Low	Low
Bergman and Chan (2021)	Low	Low	Low	Low	Low	Low
Bergman and Rogers (2016)	Some concerns	Some concerns	Low	Low	Low	Some concerns
Berlinski, Busso, Dinkelman, and Martinez (2022)	Low	Low	Some concerns	Low	Low	Some concerns
Berlinski, Busso, Dinkelman, and Martinez (2021)	Low	Low	Some concerns	Low	Low	Some concerns
Beuermann et al. (2015)	Low	Low	Low	Low	Low	Low
Borzekowski (2018)	Some concerns	High	Low	Low	Low	High
Borzekowski, Singpurwalla, Mehrotra, and Howard (2019)	Some concerns	Low	Low	Some concerns	Low	Some concerns
Büchel, Jakob, Kuhnhanss, Steffen, & Brunetti (2022)	Some concerns	Low	Low	Low	Low	Some concerns
Cardim, Molina-Millán, and Vicente (2023)	Some concerns	Low	Low	Some concerns	Low	Some concerns
Carrillo, Onofa, and Ponce (2010)	Some concerns	Low	Low	Low	Low	Some concerns
Chambers, Cheung, Gifford, Madden, and Slavin (2006)	Low	Low	Low	Low	Low	Low
Chambers et al. (2008)	Some concerns	Low	Low	Low	Low	Some concerns
Cilliers et al. (2022)	Low	Low	Low	Low	Low	Low
Cristia et al. (2017)	Some concerns	Low	Low	Low	Low	Some concerns
de Hoop et al. (2023)	Some concerns	Low	Low	Low	Low	Some concerns
Derksen, Leclerc, and Souza (2020)	Low	High	Some concerns	Low	Low	High
Duflo, Hanna, and Ryan (2012)	Low	Low	Low	Low	Low	Low
Gortazar et al. (2022)	Low	Low	Low	Some concerns	Low	Some concerns
Ibe and Abamuche (2019)	High	Low	Low	Low	Low	High
Ito, Kasai, and Nakamuro (2021)	Low	Some concerns	Low	Low	Low	Some concerns
Johnston and Ksoll (2022)	Some concerns	Low	Low	Some concerns	Low	Some concerns
Kraft and Monti-Nussbaum (2017)	Low	Low	Some concerns	Low	Low	Some concerns
Kumar and Mehra (2018)	Low	Some concerns	Low	Low	Low	Some concerns
Lai, Luo, Zhang, Huang, and Rozelle (2015)	Low	Low	Low	Low	Low	Low
Lai et al. (2016)	Some concerns	Low	Low	Low	Low	Some concerns
Lai et al. (2013)	Low	Low	Low	Low	Low	Low
Linden (2008)	Low	Low	Low	Low	Low	Low
Linebarger, Piotrowski, and Greenwood (2010)	Low	Low	Low	Some concerns	Low	Some concerns
Malamud et al. (2019)	Some concerns	Low	Some concerns	Low	Low	Some concerns
McManis and McManis (2016)	High	Low	Some concerns	Low	Low	High
Miller and Robertson (2011)	Some concerns	Low	Some concerns	Low	Low	Some concerns

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Study	Risk of bias arising from the randomisation process	Risk of bias due to deviations from the intended intervention	Missing outcome data	Risk of bias in the measurement of the outcome	Risk of bias in the selection of the reported results	Overall risk of bias
Mo et al. (2020)	Low	Low	Low	Low	Low	Low
Mo, Huang, et al. (2015)	Low	Low	Low	Low	Low	Low
Mo et al. (2013)	Low	Low	Low	Low	Low	Low
Mo et al. (2014)	Some concerns	Low	Low	Low	Low	Some concerns
Mo, Zhang, et al. (2015)	Low	Low	Low	Low	Low	Low
Muralidharan, Singh, and Ganimian (2019)	Low	Low	Low	Low	Low	Low
Naik, Chitre, Bhalla, and Rajan (2020)	Some concerns	Low	Low	Low	Low	Some concerns
Piper, Simmons Zuilkowski, Kwayumba, and Strigel (2016)	Some concerns	Low	Low	Some concerns	Low	Some concerns
Pitchford (2015)	High	Low	Low	Some concerns	Low	High
Riley (2018)	Some concerns	Low	Low	Low	Some concerns	Some concerns
Rouse and Krueger (2004)	Low	Low	Some concerns	Low	Low	Some concerns
Rutherford et al. (2014)	Low	Low	Low	Low	Low	Low
Santana et al. (2019)	Low	Low	Some concerns	Low	Low	Some concerns
Schacter et al. (2016)	High	Low	High	Low	Low	High
Seo (2017)	Low	Low	Some concerns	Low	Low	Some concerns
Setren (2023)	Low	Some concerns	Some concerns	Low	Low	Some concerns
Silander et al. (2016)	High	Low	Some concerns	Some concerns	Low	High
Verhallen and Bus (2010)	Some concerns	Low	Low	Low	Low	Some concerns
Wolf, Aber, Behrman, and Tsinigo (2019)	Low	Low	Low	Some concerns	Low	Some concerns
Yang et al. (2013)	Some concerns	Low	Low	Low	Low	Some concerns

Appendix D. Quality assessment for quasi-experimental studies (ROBINS-I)

Study	Bias due to confounding	Bias in selection of participants into the study	Bias in classification of interventions	Bias due to deviations from intended interventions	Bias due to missing data	Bias in measurement of outcomes	Bias in selection of reported results	Overall bias
Bianchi, Lu, and Song (2022)	Low	Low	Low	Low	Low	Low	Low	Low
Blimpo, Gajigo, Owusu, Tomita, and Xu (2020)	Low	Moderate	Low	Low	Low	Low	Moderate	Moderate
Brown et al. (2020)	Low	Moderate	Low	Low	Moderate	Low	Low	Moderate
Lehrer, Mawoyo, and Mbaye (2019)	Low	Moderate	Low	Low	Moderate	Low	Low	Moderate
Leuven et al. (2007)	Low	Low	Low	Low	Low	Low	Low	Low
Lysenko et al. (2019)	Low	Moderate	Low	Low	Moderate	Low	Low	Moderate
Macaruso et al. (2006)	Low	Moderate	Low	Low	Moderate	Low	Low	Moderate
Ntaila and Mbaraka (2023)	High	Moderate	Low	Low	Moderate	Low	Low	High

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Study	Bias due to confounding	Bias in selection of participants into the study	Bias in classification of interventions	Bias due to deviations from intended interventions	Bias due to missing data	Bias in measurement of outcomes	Bias in selection of reported results	Overall bias
Schacter and Jo (2016)	Low	Low	Low	Low	Low	Low	Low	Low
Wennersten, Quraishy, and Velamuri (2015)	Low	Low	Low	Low	Low	Low	Low	Low

Data availability

Data will be made available on request.

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