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Effects of Educational Technology on Students' Academic Achievement in Agricultural Education: A Meta-analysis

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Abstract

The use of educational technology is essential in education, and numerous studies have demonstrated the benefits and effects of implementing educational technology in general education settings. However, there is a research gap concerning the investigation of its impact in the field of agriculture using the meta-analysis method. To address this research gap, we conducted a comprehensive meta-analysis investigating the effect of educational technology on students' academic performance in agricultural education from 2000 to 2022. The study included 14 studies, and the average mean effect size was found to be 0.23 for the fixed-effect model and 0.21 for the random-effect model. This average effect size suggests that the use of educational technology has a positive impact on students' academic performance in agricultural education. Variables such as subjects, educational level, types of educational technology, and sample size were used for moderator analysis. The findings revealed that all four variables significantly moderate the effect size. Considering these results, implications for further research and classroom practice are provided.

Introduction

Educational technology (ET), as extensively documented across numerous scholarly contributions continues to hold significant relevance within contemporary classroom settings for the role of facilitating teaching and learning, and is projected to maintain its importance in the foreseeable future (Amin, 2019; Hannafin & Savenye, 1993; Hoon, 2008; & Xu et al., 2023). To provide befitting descriptions of the prevalent ET based on the era, several studies have captured unique attributes in their definitions such as the one given by Ely (1963) when he defined audiovisual communications (a form of ET) as "the branch of educational theory and practice primarily concerned with the design and use of messages, which control learning process" (p. D-25). The Association for Educational Communications and Technology (AECT, 1977) in their definition also sought to emphasize the need to bridge the "theory and practice" gap in the conceptualization and use of ET. Other studies have explored different practical aspects of ET, including laptop initiatives (Keengwe et al., 2012), utilization of mobile apps (Domingo & Garganté, 2016), and the implementation of multimedia (Malik & Agarwal, 2012), with the goal of understanding how these

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technologies work together to enhance the teaching and learning experience and to improve students' academic achievements.

In the field of agricultural education, which has as its core focus the equipping of students at various levels with the latest skills for careers in agriculture, food, and natural resources (AFNR), especially through the three-circle model of instruction (Baker et al., 2012; Figland et al., 2020; Rivera Comas, 2022; Rose, 2014; Swafford, 2018), the quest to incorporate the use of ET in the discipline has also been persistent. Different researchers in the field have tried to understand how ET like smartphone applications (Smith, Blackburn, et al., 2018), online and distance education (Kelsey et al., 2011), multimedia, virtual reality, mobile devices and interactive study guide (Vickrey et al., 2018) could impact students' learning. Furthermore, in a bid to achieve the goal of ET-enhanced teaching and learning process, or at least explore the possibilities derivable from the synergistic combination, studies such as those of Alston et al. (2003), Birkenholz & Stewart (1991), and Wells & Miller (2020) have found differing levels of availability and ET usage among pre-service teachers; the studies have also identified barriers such as lack of funds and limited expertise in the use of ET, and recorded a mixture of favorable responses as well as some levels of uncertainties towards ET by teachers in a school-based agricultural education (SBAE) settings.

While some studies have reported positive outcomes from using ET in agricultural education, such as increased self-efficacy through mobile learning (Irby & Strong, 2013), higher academic achievement through ET-based teaching (Safari et al., 2017), and improved teaching efficiency (Murphy & Terry, 1998), some other authors have questioned its necessity and impact on students' academic achievement. Shatri (2020) for instance found that ET use can reduce concentration and take up a lot of time. Jin and Bridges (2014) also noted that while ET can have some advantages for problem-based learning, the challenges such as complex scenarios, infrastructure requirements, and the need for staff and student support may make the advantages weigh less than the disadvantages.

The absence of a definitive, converging stance on the clear and measurable impact of ET on academic achievement in agricultural education, as discussed above, underscores the need for further research. This meta-analysis therefore aims to fill this gap by systematically examining the factors that determine the most significant effects of ET usage on students' academic achievements in agricultural education.

Literature Review

Educational Technology in Agricultural Education

Key stakeholders in the agri-food industry are at the forefront of ensuring a paradigm shift in the ways agricultural graduates are prepared to meet future industry demands. Alston et al. (2003) noted that the United States' top position in agriculture is partly due to its strong infrastructure for creating and implementing new technologies, and the secondary school agricultural education being a key element of this exceptional system. Moreover, Alston et al. (2003) highlighted that researchers have shown that local school curricula and teaching methods have not kept up with the fast-paced technological advancements in the agricultural sector over the past decade, hence, the necessity of developing new instructional methods to sustain the effectiveness of agricultural education (National FFA Organization, 1999; National Research Council, 1988).

Since the time Birkenholz & Stewart (1991) conducted a thorough review of the instructional technology used in agricultural departments in schools, which included microcomputers, modems, printers, overhead computer projection units, VCR players, cameras, amplified telephones, and more, there have been significant advancements in the range of educational technology utilized in classrooms. ET such as multimedia presentations (Marrison & Frick, 1994; Patel & Patel, 2006; Shanthy & Thiagarajan, 2011), virtual tours (Nguyen et al., 2023; Schütz et al., 2022), virtual reality (VR) (Stone et al., 2022; Strong et al., 2022; Wells & Miller, 2020), simulations and digital game-based learning (Bunch et al., 2014, 2016; Klerkx, 2021; Klit et al., 2018) enable interactive and immersive learning. These technologies also offer personalized learning, allowing students to explore learning concepts at their own pace, while educators can track progress effectively (Bhutoria, 2022; Haleem et al., 2022; Milliken et al., 2023; Safari et al., 2017).

Effect of ET on Students' Learning Outcomes

According to Cheung and Slavin (2012), there has been extensive research on the effectiveness of ET applications, including computer-assisted instruction (CAI), for improving learning outcomes since the 1980s. Among such studies measuring the impact of ET on learning outcomes are previous meta-analyses that have reported the impact of ET on students' academic achievements measured across different topics. These studies (Table 1), which have mostly been conducted in the general field of education, indicate positive impacts (except Tamim et al., 2021) of ET on students' academic achievement, with effect sizes ranging from -0.41 to +0.93. Tamim et al. (2021), however, stands as an outlier; they found an overall negative effect size (-0.41) from 52 meta-analyses in their study. Their finding was, however, predictable as it was a meta-analysis of meta-analyses (second-order meta-analysis), and the authors appropriately acknowledged the potential for inherent limitations in their methodology.

Lakens (2013) noted effect sizes are an important outcome of empirical studies over mere statistical significance because researchers use standardized effect sizes to communicate the practical implications of their findings on daily life. Additionally, these effect sizes enable meta-analysis and inform the design of new studies.

In meta-analyses that measure the effect of ET on learning outcomes, it is important to consider domain subjects as a moderating variable. Chauhan (2017) highlighted this, noting that domain subjects can help establish the relative learning effectiveness of ET across different subjects. Chauhan's study showed impressive results, indicating predominantly positive and low to medium effect sizes in almost all domain subjects studied, including general studies, science, social studies, language, mathematics, and science and technology. However, no significant effects were observed in the fields of music and arts. Meanwhile, results from the study by Zheng et al. (2022) discovered how technology-assisted learning greatly enhances academic performance, with the most significant impact observed in social science. On the other hand, engineering, technology, and natural sciences had only a moderate effect. These two findings (Chauhan, 2017 & Zheng et al., 2022) suggest that technology-based learning could have a significant impact in various academic domains in the future. Some other meta-analyses measuring the impact of ET on students' learning outcomes that have considered domain subjects are those of Lee et al. (2022), Liu et al. (2022), Ozdemir et al. (2018) and Xu et al. (2022).

Previous meta-analyses have also examined the significance of educational levels as a moderator on the overall effect size. Researchers like Garzón et al. (2019), Xu et al. (2022), Bayraktar (2001), and Sahin and Coban (2020) all investigated how educational levels from early childhood education to the doctoral level influence the impact of ET on learning outcomes. While some of these meta-analyses agree that there is no significant difference across different educational levels, suggesting that ET has a significant impact on learning outcomes regardless of the level of education, some minor distinctions may arise upon closer examination. For example, Garzón et al. (2019) discovered that primary education level students were the most targeted group in their meta-analyses on the use of augmented reality (AR). However, Xu et al. (2022) found that junior high school students were the most targeted educational level in their study which covered 35 studies. Cheung and Slavin (2012) have aptly noted that while the emphasis on the individualization of the student's pace of learning has very much been touted as the benefit of ET such as computer-aided instruction, this could either be a pro or a con. Unless the teacher can tailor the instructional needs of the individual students through the use of the most appropriate ET, the purpose of learning will be defeated.

Table 1

Selected Previous Meta-analyses on the Impact of ET on Different Learning Outcomes

Meta-analysis	Subject	Educational Level	ET Type	Sample Size	Outcomes	Effect Size
Tamim et al., 2021	General (meta-analyses on ET)	All (primary to higher education)	Not specified	52	Non-specific	-.41
Cheung & Slavin, 2012	Education	K-12	Not specified	84	Reading outcomes	.11
Chauhan, 2017	Multiple subjects/disciplines	Elementary students	Not specified	122	Learning effectiveness	.55
Ni et al., 2022	Chinese ESLL	K-12	Not specified	35	Reading achievement	.37
Xu et al., 2019	Adult ELL	Adults	Not specified	16	Writing quality	.93 1.28
Major et al., 2021	Learning in low- and middle-income countries	8-15 years old students	Computer-assisted learning (CAL), tablet, software and computer applications	15	Personalized learning	.18
Lee et al., 2022	ELL	K-12	Not specified	36	Literacy development	.47
Liu et al., 2022	Technology and creative core subjects	Not specified	Multimedia	50	Creative performance	.59
Ozdemir et al., 2018	Natural and social sciences	Primary to undergraduate	Augmented reality	16	Learning process	.50
Xu, et al., 2022	Sciences	Preschool to college/university	Augmented reality	35	Science learning	.73
Garzon et al., 2019	Natural sciences, statistics, and mathematics	Early childhood education to doctoral level	Augmented reality	61	Learning process	.64
Schmid et al., 2014	STEM and non-STEM	Postsecondary education	Not specified	1105	Achievement and attitude outcomes	.27

Past meta-analyses have identified various types of ET that may impact students' academic achievements such as online learning and distance education technology (Johnson, 2008 & Pei & Wu, 2019); augmented reality (Garzón et al., 2019; Ozdemir et al., 2018; Xu et al., 2022); technology/computer-assisted instruction (Bayraktar, 2001; Lee et al., 2022; Major et al., 2021; Young, 2017; Zheng et al., 2022); digital game-based learning (Byun & Joung, 2018; Kim et al., 2021; Turgut & Temur, 2017; Z. Xu et al., 2020); digital storytelling (Sahin & Coban, 2020); and mobile apps and mobile devices (Alrasheedi & Capretz, 2018; Alzahrani & Laxman, 2016; Chee et al., 2017).

Another variable that has been found to significantly impact the overall effect size in previous meta-analyses is the sample size (Cheung & Slavin, 2013; Liao, 2007; Slavin & Smith, 2009). It has been observed that studies with small sample sizes tend to produce much larger effect sizes than those with bigger sample sizes, according to previous research cited by Cheung and Slavin (2013).

Unfortunately, there has not been any meta-analysis conducted on the subject of ET in the field of agricultural education, unlike other fields of pure and applied education. This has resulted in a lack of knowledge on the subject. This current meta-analysis is therefore very timely as it notably contributes to the body of knowledge. It systematically examines overall and moderator effect sizes to determine the impact of ET on students' academic achievement in agricultural education.

Theoretical Framework

The theoretical framework underpinning this meta-analysis is grounded in the constructivist theory of learning (Piaget & Cook, 1952; Vygotsky & Cole, 1978), which posits that knowledge is actively constructed by learners through interaction with their environment and reflection upon their experiences. This theoretical perspective views ET not just as vessel for content delivery but as a platform for active exploration, enabling learners to engage with concepts in a manner that promotes deeper understanding and knowledge construction (Yu & Xu, 2022). This perspective directs our focus to how ET facilitates learning processes such as active engagement, social negotiation, and personalized learning experiences, thereby impacting students' learning outcomes (Bernard et al., 2014; Cheng et al., 2019; Cheung & Slavin, 2013; Saraç, 2018; Shi et al., 2020; Yu & Xu, 2022).

Ni et al. (2022) further noted that the use of ET which is rooted in constructivism, prioritizes learning through active participation, practical application, and knowledge acquisition, thereby placing greater emphasis on student-centered learning, allowing learners the freedom to create their own knowledge without rigid constraints. By integrating constructivist theory with the evaluation of the impact of ET on students' learning outcomes, this analysis seeks to uncover how ET has been used and how it can be optimally leveraged to create engaging, meaningful learning experiences. The goal is to provide insights into the design and implementation of technology-enhanced learning that not only transmits information but actively involves learners in the construction of knowledge. Through this investigation, we aim to contribute to the ongoing dialogue on educational practice, especially in agricultural education by identifying those ETs that have made the most impact on students' learning outcomes and understanding the learning contexts and environments under which these have been possible.

Research Questions

This study aims to investigate the impact of educational technology on students' learning outcomes in agricultural education through a meta-analytic approach. Specifically, we seek to determine whether educational technology enhances students' academic achievement and to explore how various factors, such as subject matter, educational level, types of educational technology, and sample size, moderate this effect.

Two research questions guided this study.

1. Do educational technology applications improve academic achievement in agricultural education?
2. How do substantive and methodological characteristics of the studies, such as subjects, educational level, types of educational technology, and sample size, affect the estimated effect?

Methods

Literature Search

To evaluate how educational technology impacts the academic achievements of students studying agricultural education, we conducted a thorough literature review from 2000 to 2022. Previous studies have suggested that educational technology has developed fast in the past years (Alston & English, 2007; Wingard, 2004). Thus, we chose the time frame to include only the most recent studies since 2000. We searched the five databases covering the disciplines of agriculture and education: CAB Abstracts (Ovid), AGRICOLA (EBSCO), ERIC (EBSCO), Education Source (EBSCO), and Web of Science Core Collection (Web of Science).

In this meta-analysis, educational technology (ET) is defined as the practice of using technological processes and resources like computers, video projectors, and the internet to facilitate learning and improve performance (Januszewski & Molenda, 2008). These technologies are placed in the classroom with the purpose of enhancing teaching and learning. This study posits that educational technology includes both a process, such as e-learning and virtual simulations, as well as instructional technology/devices like projectors, iPads, smartphones, computers, mobile devices, and videos.

Inclusion & Exclusion Criteria

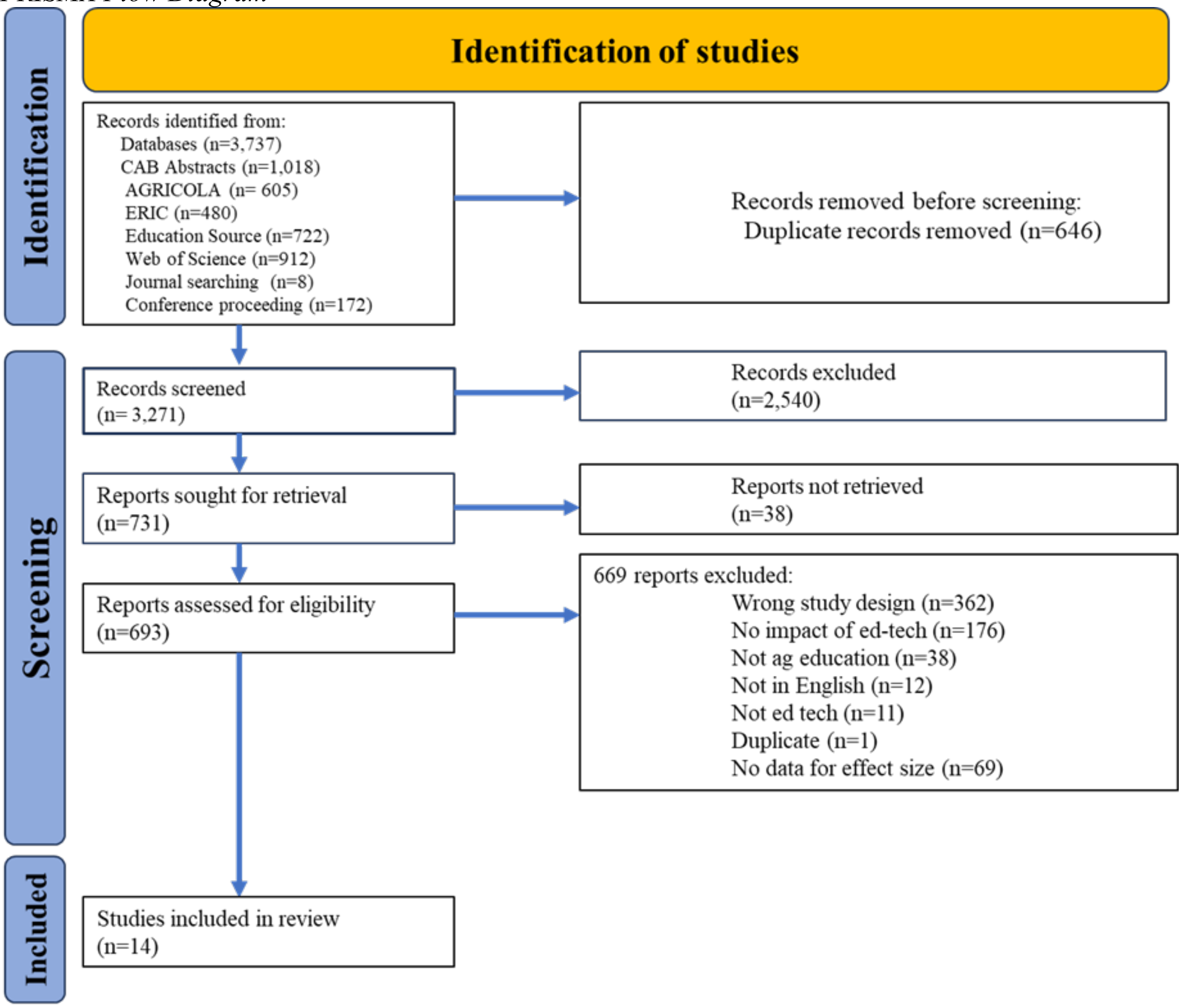
Studies selected for this meta-analysis satisfied the following criteria:

- The selected studies must have examined the effect of educational technology on agricultural education.
- The included studies must have been published in a journal, conference proceeding, or dissertation (master and doctorate degree thesis) between 2000 and 2022.
- The included studies must report a method of assessment of educational technology's impact/effect on agricultural education.
- Included studies needed to report detailed information on the effect of educational technology on academic achievements in agricultural education, which include the sample size, experimental design, and detailed results.
- The included articles without a control group were excluded from the study.
- Articles with academic performance results such as final score, knowledge test score were included.
- Studies with self-reported achievement scores were excluded.
- Articles without enough information to calculate the effect size were excluded.

To ensure a valuable systematic review, authors should transparently, completely, and accurately document the review's purpose, methodology (including study identification and selection), and findings (such as study characteristics and meta-analysis results), thus PRISMA guidelines was recommended (Page et al., 2020). As presented in Figure 1, we initially extracted articles, conference proceedings and dissertations from different databases (n=3737). After using our inclusion and exclusion criteria, we have 14 independent studies for included studies.

Figure 1

PRISMA Flow Diagram



Coding of Studies

We aim to explore the most important factors that influence the effectiveness of educational technology in agriculture education. The magnitude of effect sizes reported in previous studies can be influenced by various factors, leading to a complicated and varied outcome. Several factors that can affect the intervention's effectiveness include grade levels (e.g., K-12 or higher education setting)(Cheung & Slavin, 2012; Sahin & Coban, 2020)), subject domains (such as math or language, science or general)(Xu et al.,2022), types of educational technology (such as mobile learning, simulation, or online education), the educational setting (formal or informal) (Chauhan, 2017) of the intervention implementation. For instance, subject domains may have varying levels of compatibility with different types of educational technology, impacting the outcomes (Chauhan, 2017). Furthermore, the specific type of educational technology used, whether it's mobile learning, simulation-based learning, or online education, can influence the effectiveness of the intervention (Ni et al., 2022). Based on previous literature, subjects, educational level, types of educational technology, sample sizes are identified as the important variables to be coded in this manuscript.

Subjects. We categorized the subjects within the agricultural field into distinct areas, namely agricultural science, agricultural engineering, agricultural leadership, education and communication (ALEC), and agricultural economics and finance.

Educational level. We coded educational levels as secondary, undergraduate, graduate, and mixed. These categories allow us to examine the impact of educational technology across different levels of education.

Types of educational technology. Educational technologies were grouped into online/distance education, simulation/digital games, multimedia & traditional technology, mobile technology, and the flipped classroom.

Sample size. We adhered to widely recognized guidelines in the educational field for categorizing the sample sizes of the included studies. Studies with fewer than 100 participants were grouped into the small sample group, studies with 100-250 participants were classified as the medium sample group, and studies with over 250 participants were designated as the large sample group (Cheung & Slavin, 2012; Xu et al., 2020).

Calculation of Effect Sizes and Statistical Analysis

Using the means and standard deviations reported, we employed the methods outlined by Lipsey and Wilson (2001) to compute an unbiased effect size (Cohen's d). Out of 14 studies, eight used pre-test and post-test designs, whereas six studies only had post-test measures. Two studies did not report the pre-test scores. To ensure consistency, we employed the post-test scores of the treatment and control groups to calculate effect size.

The effect sizes included in our analysis were mostly independent, except for one article that contributed two effect sizes in different measure domains (science and math). Due to the small number of dependent effect sizes, we employed single-level meta-analysis instead of multivariate meta-analysis. In total, we included 14 effect sizes for analysis. The software R version 4.3.0 (R Core Team, 2022) was used for data analysis.

In our analysis, we reported both fixed effect model and random effect model results to assess the overall effectiveness of the educational technology interventions. Fixed effect model assumes that each study has the same underlying effect, the variability comes from sampling error, random effect model allows a variance in both the estimated and the true effect between the individual studies (Brockwell & Gordon, 2001; Dignath & Buttner, 2008). Fixed effect models risk producing type I error rates if effect sizes are heterogeneous (Cohn & Becker, 2003; Higgins & Thompson, 2004). If assumption for random-effect model is violated, error variance may be overestimated, and confidence intervals may be too conservative (Overton, 1998). Thus, we used both models considering those concerns. The fixed effect model was used for moderation analysis for moderators. Homogeneity tests were conducted to determine if the effect sizes obtained from different studies provided consistent estimations of the same population effect size, with a statistically significant Q suggesting the heterogeneity. The heterogeneity suggested significant variations in the effect sizes for the included studies and the suitability of conducting moderation analysis to explain the variation in the effect sizes.

We employed two methods to check for publication bias. First, we examined a funnel plot to evaluate the expected relationship between effect-size magnitude and their corresponding standard errors. Second, we conducted a quantitative assessment method using Egger's regression test (Egger et al., 1997) to estimate the likelihood of publication bias.

Results and Discussion

We present the overall effect indicated by the mean effect size for the 14 included studies, using both fixed effect and random effect models. These results are then compared with previous literature regarding the direction and magnitude of the effect size. Second, we demonstrate the result of moderator analysis regarding subjects, sample size, educational level, types and educational technology and provide details of possible reasons that could explain how those variables affect the effect of educational outcomes in the agriculture education setting. Lastly, we report the result of publication bias analysis.

Overall Effect

Fourteen studies were included in the meta-analysis, contributing a total of 14 effect sizes. The studies were published between 2000-2020 and all included both a control group and an experimental group. Eight studies used pre-test and post-test designs, while six studies only had post-test measures. The post-test exams were achievement tests that assess students' knowledge. The total number of participants included in the analysis was 1808, with sample sizes ranging from 8 to 317.

For the overall meta-analysis, both the fixed and random effect models were used. Figure 2 demonstrated overall effect size result for fixed effect model and Figure 3 demonstrated overall effect size result for random effect model from R. As is reported in Table 2, the fixed effects weighted effect size was 0.23 (p<.001, SE = 0.05), with a 95% confidence interval of [.13, .33]. When Effect Size equals 0.2, it is small; when Effect Size equals 0.4, it is medium; when Effect Size equals 0.6, it is large (Haiti, 2009). The weighted effect size (d = .23) indicated that educational technology-based interventions have a small positive effect on participants' learning outcomes based on Hattie's categorization of small, median and large effect size (Hattie, 2009) compared to traditional teaching methods. The overall random effects weighted effect size was 0.21 (p = .57, SE = .37), with a 95% confidence interval of [-.51, .93]. For both random effect model and fixed effect model, heterogeneity tests revealed significant heterogeneity among the 14 included studies ($Q(df$=13) =376.62, p<.001). The heterogeneity suggested significant variations in the effect sizes for the included studies. The heterogeneity results indicated the suitability of conducting moderation analysis to explain the variation in the effect sizes. In short, the moderator analysis is to examine if and how subjects, sample sizes, types of educational technology and educational level as moderators can affect the effect of educational technology on academic performance in agriculture education.

Table 2

Average Effect Sizes and Heterogeneity Statistics

Model	**Average Effect Size (ES)**	**Standard Error (SE)**	**95% CI**	***p***	**Test of heterogeneity**		
					Q	***df***	***p***
Fixed	.23	.05	[.13, .33]	<.001	376.62	13	<.001
Random	.21	.37	[-.51, .93]	.57	376.62	13	<.001

Figure 2

Effect Size Result for Fixed Effect Model

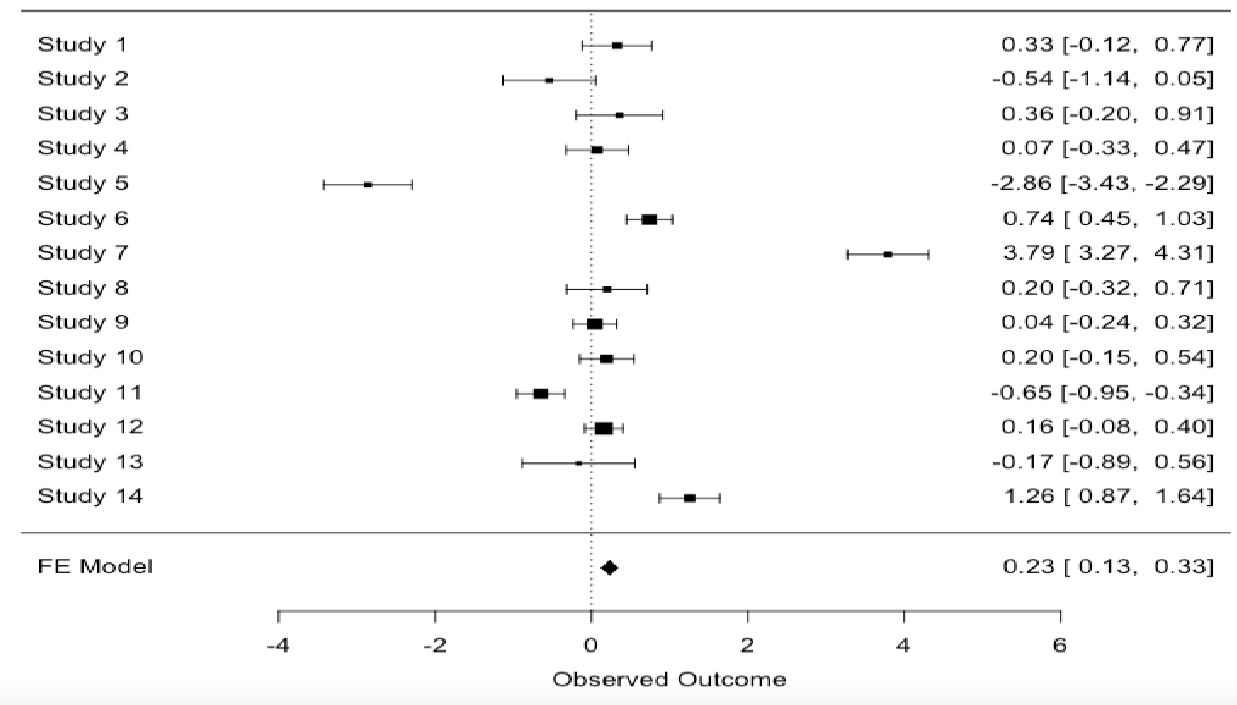
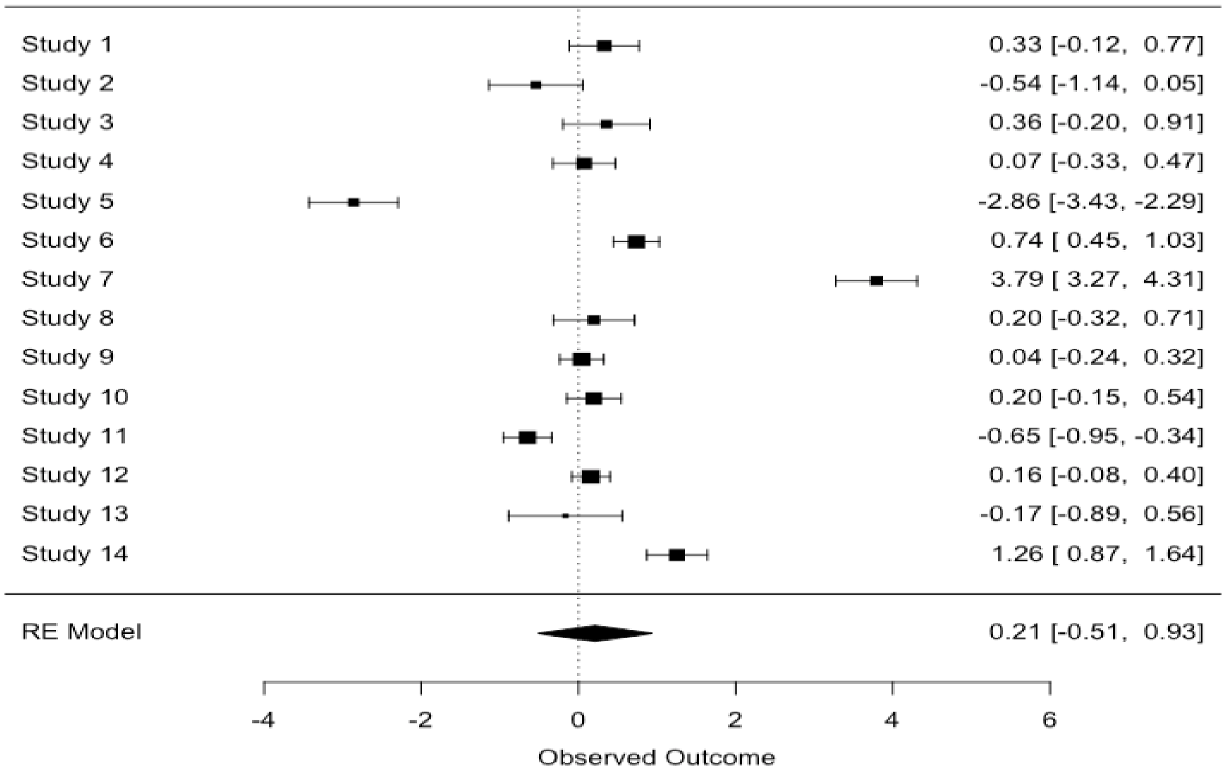


Figure 3

Effect Size Result for Random Effect Model



Our study aligns with previous reviews in the general education field, which have shown consistent findings regarding the effectiveness of educational technology. These reviews have reported small, positive effect size: ES = .16 (Cheung & Slavin, 2012), ES = .25 (Kulik& Kulik, 1991), ES = .18 (Becker, 1992), ES = .16 (Ouyang, 1993), ES = .12 (Fletcher-Finn & Gravatt, 1995), ES = .13 (Soe et al., 2000), ES = .19 (Blok et al.,2002), ES = .27 (Schmid et al., 2014). For instance, Major et al., (2020) found that technology-supported personalized learning intervention has a significant positive effect (ES = .18) on students' learning. Schmid et al. (2014) found a small positive effect (ES = .27) in higher education for classroom applications. However, there are also studies that reported medium to large effect sizes. Chauhan (2017) reported a medium effect on learning effectiveness for elementary students. Liao et al. (2007) synthesized computer applications and reported a medium effect size (ES = .449) in elementary school in Taiwan. Lee et al. (2022) investigated technology-integrated instruction on literacy development for K-12 English language learners and found a positive effect size of 0.47. Zheng et al. (2022) reported that technology-facilitated personalized learning had an effect size of 0.67. Xu et al. (2019) suggested that technology applications produced a large effect size (ES = 1.28) on adult English language learners' writing quality.

The effectiveness of educational technology can be influenced by various factors, leading to a complicated and varied outcome. Various factors including grade levels, subject domains, types of educational technology can play a holistic role in shaping the impact of educational technology on learning outcomes in complicated aspects. Given the complexity and variability of these factors, conducting a moderator analysis becomes essential to explore which specific factors contribute to the variability of the effect sizes observed in included studies. By analyzing these moderators, we can gain a deeper understanding of how different factors influence the effectiveness of educational technology interventions and make more informed decisions regarding their implementation.

Moderator Analysis

We examined four substantive and methodological characteristics (subjects, educational level, sample size, and types of educational technology) as moderators of effect sizes. All the variables were categorical. Table 3 provides the characteristics of included studies. A fixed effect model and a random effect model were used.

Subjects. As is shown in Table 4, the subject moderator analysis revealed a significant amount of effect-size heterogeneity in effect sizes ($Q_b(3) = 22.64$, $p < .001$), indicating variations among different subject groups, namely agricultural science, agricultural engineering, ALEC, and agricultural economics and finance. The effect size for ALEC ($n = 4$) was the largest ($d = .66$), followed by agricultural economics and finance ($n = 1$, $d = .33$), agricultural engineering ($n = 2$, $d = .11$), and the smallest effect size was found in agriculture science ($n = 7$, $d = .07$).

Our study found significant differences in effect sizes across different subject matters, which aligns with Bayrakta (2001). However, some other studies did not report significant differences in effect size in different subjects, such as Zheng et al., (2022), Ozdemir et al. (2018), Turgut and Temur (2017), and Wang et al. (2023).

Furthermore, our findings revealed that educational technology generated a larger effect in education subjects than engineering and science subjects, which is consistent with Låg & Sæle (2019), who reported effect sizes of 0.53 for humanities, 0.42 for social science, and 0.32 for STEM disciplines. However, this contrasts with Chauhan (2017), which suggested that the use of technology led to a medium effect size for science and technology (*ES* = 0.44) and smaller effect for social studies (*ES* = .27), as well as Garzón et al. (2019), who reported the smallest effect

Table 3

List and Description of Included Studies

Study ID	Publication	Subjects	Educational Level	Types of Ed Tech	Sample Size	ES
1	Armah (2001)	agricultural economics and finance	undergraduate	multimedia & traditional technology	large	.33
2	Wingenbach (2000)	ALEC	undergraduate	multimedia & traditional technology	small	-.54
3	Wells & Miller (2020)	agricultural engineering	mixed	simulation/digital games	medium	.36
4	Bunch et al. (2014) I	agricultural science	mixed	simulation/digital games	medium	.07
5	Bunch et al. (2014) II	agricultural science	mixed	simulation/digital games	medium	-2.86
6	Boyd & Murphrey (2002)	ALEC	secondary	multimedia & traditional technology	medium	.74
7	Wickenhauser et al. (2020)	agricultural science	undergraduate	online/distance education	medium	3.79
8	Namuth-Covert et al. (2019)	agricultural science	undergraduate	flipped classroom	medium	.20

9	Mueller et al. (2015)	agricultural engineering	secondary	online/distance education	small	.04
10	Klit et al. (2018)	agricultural science	undergraduate	simulation/digital games	medium	.20
11	Davis et al. (2012)	agricultural science	undergraduate	simulation/digital games	medium	-.65
12	Smith et al. (2018)	agricultural science	undergraduate	mobile technology	large	.16
13	Witt et al. (2011)	ALEC	graduate	simulation/digital games	small	-.17
14	Harder & Bruening (2011)	ALEC	undergraduate	online/distance education	medium	1.26

Note: when Effect Size = .2, it is small; when Effect Size = .4, it is medium; when Effect Size = .6, it is large (Haiti, 2009).

Table 4

Results of Moderation Analyses

Moderator	***k***	***df***	***d***	***se***	**95%CI**	I^2	$p_{subgroup}$
Subjects						97.17 %	< .001
Agriculture Science	7	6	.07	.07	[-.07, .21]		
Agricultural engineering	2	1	.11	.13	[-.14, .36]		
Agricultural leadership, education and communication	4	3	.66***	.11	[.45, .87]		
Agricultural economics and finance	1	0	.33	.23	[-.12, .77]		
Educational Level						97.04 %	< .001
Secondary	2	1	.38***	.10	[.17, .58]		
Undergraduate	8	7	.36***	.07	[.23, .49]		
Graduate	1	0	-.17	.37	[-.89, .56]		
Mixed	3	2	-.58***	.14	[-.86, -.29]		
Types of Ed Tech						96.69 %	< .001
Online/distance education	3	2	1.00***	.11	[.79, 1.20]		
Simulation/digital games	6	5	-.38***	.08	[-.56, -.21]		
Multimedia & traditional technology	3	2	.45***	.12	[.22, .67]		
Mobile technology	1	0	.16	.12	[-.08, .40]		
Flipped classroom	1	0	.20	.26	[-.32, .71]		
Sample Size						97.01 %	< .001
Small	3	2	-.08	.12	[-.31, .16]		
Medium	9	8	.34***	.07	[.21, .47]		
Large	2	1	.20	.11	[-.02, .41]		

*Notes: k - number of effect sizes; * p<.05; *** p<.001; df= degree of freedom; Significance tests for the effects should be interpreted with caution for df < 4.*

Size for education. Garzón et al. (2019) also identified significant differences within the field of education, with arts and humanities having the largest effect size (*ES* = .96), followed by social sciences journalism, and information (*ES* = .71), natural science, math, and statistics (*ES* = .69), Information and communication technologies (*ES* = .36), and education (*ES* = .27).

However, it is important to interpret the results for agricultural economics, finance, and agricultural engineering, and ALEC with caution due to the limited number of studies included in these subject groups. Further research with a larger number of studies, as more emerge over time, is needed to validate these findings and provide more robust conclusions.

Educational level. As shown in Table 4, the educational level moderator analysis revealed a significant amount of heterogeneity in effect sizes ($Q_b(3) = 38.48$, $p< .001$), indicating that the educational level of participants impacted the effectiveness of educational technology in agriculture education. The largest effect size was observed in the secondary group (n = 2, d = .38), followed by the undergraduate group (n = 8, d = .36). Negative effect sizes were found for graduate level (n = 1, d = -.17), and the mixed graduate level group (n = 3, d = -.58).

Our studies found significant differences in effect size in different educational levels while some studies did not find significant differences (Bayraktar, 2002; Låg & Sæle, 2019; Ozdemir et al., 2018; Wang et al., 2023; Zheng et al., 2022). Specifically, our study showed a positive medium effect size for the secondary group, which is consistent with Cheung and Slavin (2012) with an effect size of 0.31 for secondary level. Some previous studies demonstrated a large effect size for the secondary group. For example, Garzón et al. (2019) found a significant difference in different levels of education with upper secondary education yielding the largest effect size (d = .70), followed by primary education (d = .65), and undergrad level (d = .62), the smallest the lower secondary education (d = .60). Turgut and Temur (2017) also reported significant differences between high school (ES = 1.21) and middle school (ES = .66). Due to the small number of studies included in secondary, graduate and mixed groups, the negative results should be interpreted cautiously.

Types of educational technology. As shown in Table 4, the type of technology used had a significant impact on the effectiveness of interventions in agricultural education through educational technology, as indicated by the moderator analysis ($Q_b(4) = 104.73$, $p< .001$).The largest effect size was witnessed in the online/distance education group (n = 3, d = 1.00), and the smallest effect was found in the simulation/digital games group (n = 6, d = -.38). The mean effect size of the multimedia & traditional technology group (n = 3) was 0.45, the mean effect of the flipped classroom (n = 1) was 0.20, and the mobile technology group (n = 1) was 0.16.

Our study found significant differences using types of educational technology as a moderator while Liao et al. (2007) did not find such differences for different types of applications. Regarding online education, our finding showed a large effect, which is consistent with Pei and Wu (2019), that reported a large effect size of 0.68 for online learning in undergraduate medical education. In terms of traditional technology, our study reported a medium effect. That contrasts with the findings of Wang et al. (2023), who reported a significant difference between pen-and-paper and traditional technology, with a small effect size of 0.28. For the flipped classroom, our study found a positive effect, consistent with Låg & Sæle (2019), who reported a small effect (*ES* = .35). For mobile learning, our study revealed small effect. In contrast, previous studies found effect size ranges from small effect size (*ES* = .05, Hunsu et al., 2016), medium effect (e.g., *ES* = .48 (Castillo-Manzano et al., 2016), *ES* = .48 (Tingir et al. , 2017), *ES* = .48 (Castillo-Manzano et al., 2016) to large (*ES* = .80 (Yang et al., 2020), *ES* = 1.04 (Shi & Kopcha, 2022), *ES* = .69 (Ozdemir et al., 2018). For simulation/digital games, previous studies reported effect sizes ranging from small *ES* = .39 (Bayraktar, 2001) to large effects *ES* = 0.74 (Xu et al., 2022). It is important to interpret the results for sub groups like Online/distance education, Multimedia & traditional technology, mobile technology and flipped technology with caution due to the limited number of studies included in these sub-groups.

Our study revealed a significant negative (d = -.38) effect, which is surprising. Various factors might impact the quality of agricultural studies' implementation. In Bunch et al. (2014), due to dropout and incomplete data sets, the chances of committing a Type II error increased. The 10-day long intervention did not provide sufficient time to produce a magnitude of effect (Bunch et al., 2014). In Davis et al. (2012), weather constraints limited outdoor lab-based technology-infused activities, affecting the quality of intervention. Outcome measures in the study of Davis et al. (2012) might not fully reflect students' technology-infused lab experiences. Wingenbach (2000) found agriculture students performed worse using electronic media for quizzes, possibly due to discomfort with email usage before the quiz. Researchers must consider and address these factors to ensure the robustness and accuracy of their findings in the agriculture field.

Sample size. As shown in Table 4, the moderator analysis demonstrated that the sample size (the number of the participants in the study) significantly influenced the effectiveness of educational technology interventions in agricultural education (Q_b = 8.88, df = 2, p = 0.0118). The medium sample size group (n = 9) had the largest effect size (d = .34), followed by a large sample size group (n = 2) with a smaller effect size (d = .20). In contrast, the small sample size group (n = 3) had a negative and the smallest effect size (d = -.08). This suggests that larger sample sizes tend to yield more favorable outcomes in terms of the effectiveness of educational technology interventions.

The sample size plays a crucial role in determining a study's statistical power (Lan & Lian, 2010). Increasing the sample size generally leads to improved statistical power (Liao et al., 2007). However, it is important to interpret the results for the large and small sample size groups with caution due to the limited number of studies included. Further research with a larger sample size is necessary to provide more reliable conclusions regarding the impact of sample size on the effectiveness of educational technology interventions in agricultural education.

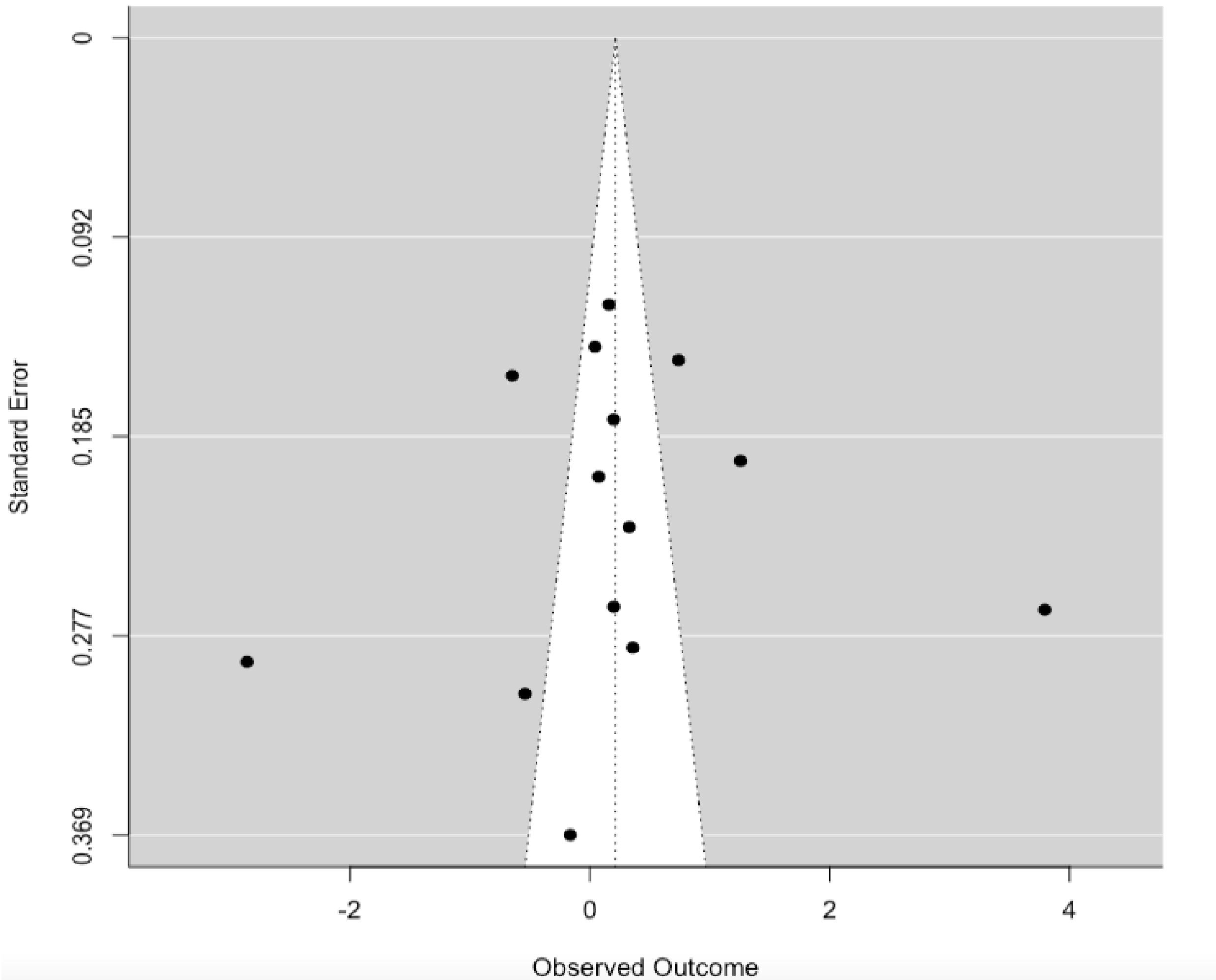
The different findings might be due to different definitions of small, medium, and large. For example, In Liao et al. (2007) sample size is group 1-50 as small, 51-100 as medium, and over 100 as large which is different from our definitions.

Publication Bias

Publication bias was investigated through funnel plot and Egger's regression test. As shown in Figure 4, the funnel plot exhibited effect-size symmetry, and the results of Egger's regression test suggested a lack of statistical significance (-.002, p = .99). These findings provide no evidence of plot asymmetry and suggest a minimal likelihood of publication bias.

Figure 4

Funnel Plot



Conclusion, Limitation and Implication

Our study aimed to examine the effectiveness of educational technology in agricultural education. The findings indicated a small yet positive effect of educational technology. Aspiring educators should consider integrating educational technology into their classrooms. Additionally, our research revealed that various factors, such as subjects, educational level, types of technology, and sample size, significantly moderate the effectiveness of educational technology interventions. Teachers should be mindful of these factors when implementing educational technology. Secondary-level education is particularly encouraged in this regard. Different types of educational technology also yield varying effects. Online or distance education, for instance, can be particularly advantageous for policymakers, educators, and relevant stakeholders. Classroom teachers should select the type of educational technology based on the learning objectives, curriculum, and learners' characteristics. Furthermore, we suggest that future researchers in similar fields opt for a medium sample size for optimal results.

Our study makes contributions to the existing literature in two ways. Firstly, it employs a comprehensive meta-analysis approach, providing a thorough investigation into the effectiveness of educational technology in agricultural education. Secondly, we successfully identified several important moderators (e.g. subjects, sample size, educational level and types of educational technology) that elucidate the effectiveness of educational technology, thus offering valuable suggestions and clear directions for both classroom practice and future research. However, it is important to acknowledge certain limitations in our study.

First, inconsistent study design in included studies might be the limitation. Some studies used pretest and posttest while some studies only have posttest. Two studies used a pretest-posttest design, but pretest scores information was not reported. Thus, the initial equivalence between experimental and control groups cannot be assessed for those without a pretest assessment. We included all the studies in the same meta-analysis for those with pretest, posttest design, and only posttest design due to lacking enough of our included studies. Future research should separate different study designs or preferably include only those with initial equivalence established with the evidence that pretests for the control and experimental group are not significantly different. Second, a small number of included studies for analysis. Our studies only included 14 independent studies due to the limited research in this field. Due to limited numbers of effect sizes in subgroup analysis, the research results should be interpreted with caution. With time passing and more flourished research in the field, future studies should employ larger sample sizes for included articles to validate the findings. Third, not all studies reported a comparable reliability indicator or fidelity of the intervention. The quality of the intervention from the studies can be questioned. Future studies investigating the effectiveness of educational technology can improve by reporting the indicators of the quality of the intervention so the conclusion of non-effectiveness can be generalized towards the educational technology itself instead of due to other factors like lacking quality of the intervention. Fourth, our included studies measured learning outcomes through achievement scores like knowledge tests. Other outcome measures like strategy use, motivation, attitude, and engagement can be explored as learning outcomes in the future.

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