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Digital learning and student outcomes: a mathematical synthesis from the last decade

Aizhan Koishybekova[1], Nazym Zhanatbekova[2], Yerlan Khaimuldanov[1], Assel Orazbayeva[3], Dariya Abykenova[4]
[1]Department of Educational Informatics, Zhetysu University named after I. Zhansugurov, Taldykorgan, Kazakhstan
[2]Department of Physics and Mathematics, Zhetysu University named after I. Zhansugurov, Taldykorgan, Kazakhstan
[3]Department of Information and Communication Technologies, Zhetysu University named after I. Zhansugurov, Taldykorgan, Kazakhstan
[4]Department of Computer Science, Pavlodar Pedagogical University, Pavlodar, Kazakhstan

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ABSTRACT

Understanding the broad effects of e-learning on educational outcomes and the contributing factors is crucial, especially given the conflicting conclusions from past research. This is important to ensure that educators and policymakers do not waste resources and focus effectively when prioritizing digital investments. Hence, this study sought to provide a comprehensive quantitative review of the extant evidence on how digital learning initiatives affect student outcomes within the cognitive domain across different subjects and educational levels. To that end, a meta-analysis was performed encompassing 17 studies spanning from 2015 to 2023, involving 1,896 participants. The quantitative synthesis was completed using a random-effects model. The results indicate a positive small to medium overall effect size (Hedge's g=.49, adjusted for publication bias) for technology-assisted interventions compared to traditional education. Subgroup analyses revealed nuances, such as higher academic gains associated with active cognitive engagement modes and potential disparities between school and higher education settings. However, no factors significantly affected the pooled effect sizes for cognitive outcomes. Nevertheless, considerable between-study heterogeneity could compromise the estimates. The meta-analysis underscores the scarcity of rigorous studies in the digital learning domain. Further research directions are outlined.

Corresponding Author:

Nazym Zhanatbekova
Department of Physics and Mathematics, Zhetysu University named after I. Zhansugurov
Zhansugurova 187a, 040009 Taldykorgan, Kazakhstan
Email: zhanatbekova@post.com

1. INTRODUCTION

The overall digitalization trend over recent decades, the SARS-CoV-2 pandemic between 2020 and 2022, and the burst of generative artificial intelligence (AI) tools since late 2022 when the 3.5 model of ChatGPT was released publicly-these phenomena taken together seem to have spawned an educational landscape that at last can be really called post-digital, that is, one "where the human and the digital are interacting, co-creating, and merging in ways that are beyond imagining" [1]. The education sector across the globe is undergoing metamorphoses in educational policy and curriculum. Nevertheless, judging by the slow adoption of even well-established technologies [2]–as illustrated by the blow to education systems when COVID-19 hit-observed even in countries like the United Arab Emirates [3], it can be assumed that a widespread shift to AI-driven learning models will not happen as quickly as one might imagine.

As researchers have noted, the integration of AI will likely complement the existing digital gap rather than bridge it [4]. Virtual assistants and mixed reality will become the fashionable agenda of education policymakers and researchers but in many educational settings, in fact, even the tools from the day before yesterday, such as WhatsApp, will remain something of a zone of proximal development for learners and educators. Moreover, the emergence of novel technologies does not necessarily lead to the extinction of older ones. For instance, AI chatbots are only an auxiliary, labor-augmenting tool that cannot yet replace, learning management systems affording student-teacher interactions (as particularly exemplified in [5]). Lastly, topical technologies, many of which were not developed recently (as is the case with chatbots), can rejuvenate established technologies. A prime example is the integration of AI into Microsoft Word.

It may be argued therefore that educators and students are now in a liminality where the latest technologies have not yet completely infused the educational environments but are gradually mingling with so-called normalized technologies. In the coming years, the ability to work with tools like educational apps will probably become a competitive edge for teachers and a sine qua non for learning in lots of academic disciplines. However, a still pending issue for academia is the influence of digital learning on educational success. Digital learning, also referred to as technology-enhanced learning or e-learning can be termed as an instructional approach that utilizes electronic media and devices as supportive environments [6].

Over the recent decennia, there has been a plethora of research on the effectiveness of digital learning on cognitive domain learning outcomes. Nonetheless, applied research has arrived at conflicting conclusions and the meta-analyses available today are narrowed in some way, focusing on specific disciplines and fields [7], [8], population [9], or both [10]. Particularly, the meta-analysis of 31 technology-enabled interventions [11] is limited to college students and nearly all the studies included in the meta-analysis did not rely on random group assignment and/or did not incorporate a pretest. Notably, one publication [12] did not describe any e-learning intervention at all, which raises concerns about the quality of the meta-analysis. Such a fragmented research field may tamper with digital investment prioritization by educators and policymakers [13]. Without a clear understanding of the overall impact and the factors influencing it, there is a risk of misallocating funds and attention, potentially affecting the quality of education provided to students and hindering digital transformation. Moreover, in light of existing trend toward AI-assisted datafication of education to make it more mechanical, predictable and manageable [14], we believe it is compulsory to comprehend the impact of previously implemented digital tools as a critical baseline before swiftly infusing recent AI-driven solutions like ChatGPT into education. Specifically, this understanding could help assess the added value that recent technologies might bring to education compared to earlier ones and establish a more robust springboard for the integration of AI into educational settings.

The present study purports to be the first to quantitatively summarize the evidence regarding the impact of digital learning on students' cognitive domain learning outcomes across various academic disciplines and levels. This contribution to educational research is expected to provide a synthesized perspective on existing evidence. It is important to note that this study exclusively considers studies that employ randomized allocation of participants as a quality filter. Additionally, the chosen time frame for the last decade is intended to minimize the inclusion of outdated technologies and approaches. Specifically, the following research questions (RQs) guided this meta-analysis:

i) What is the pooled effect size of digital learning on cognitive learning outcomes over non-digital instruction? (RQ1)
ii) Does the efficacy of digital learning vary significantly based on intervention characteristics? (RQ2)

2. METHOD

2.1. Study inclusion criteria

To be included in our meta-analytic dataset, a document had to meet the following requirements: i) report an empirical pretest-posttest controlled study lasting at least two weeks, employing random assignment and involving formal students across all education stages except preschool, without special educational needs; ii) include at least one comparison between a digital learning condition and a non-digital learning condition; iii) present at least one cognitive learning outcome measured by objective assessment across digital and non-digital groups; iv) explicitly state the components of the intervention, i.e., how the experimental group differed from the control group; v) report quantitative data sufficient for effect size calculation; and vi) be an original English-language research article published in a peer-reviewed journal between 2013 and 2023. Following Hillmayr *et al.* [10], we excluded game-based learning interventions due to the conceptual blur surrounding this technique.

2.2. Search procedures

To ensure a comprehensive and systematic search of relevant literature, the LENS database was utilized. LENS serves more than 200 million scholarly records from platforms such as PubMed and Crossref. The following search query string was applied to identify eligible sources: "((app OR apps OR tablet OR iPad OR robotic OR digital learning OR augmented reality OR mixed reality OR learning platform OR learning management system OR software OR quiz OR 3D printing OR 3D modelling OR interactive whiteboard OR interactive tabletop OR internet OR massive open online course OR MOOC OR mobile-assisted language learning OR mobile OR MALL OR Web 2.0 OR social media OR blog OR chat OR video conference OR computer supported OR computer-supported OR technology-supported OR technology supported OR e-textbook OR e-book OR ebook OR digital OR computer OR information technology OR information and communication technology OR ICT OR technology OR technology enhanced OR TEL OR technology-enhanced OR technology-based OR technology based OR virtual reality OR virtual learning OR VR OR VLE OR computer-based OR computer-assisted OR multimedia OR intelligent tutoring OR e-learning OR online learning OR simulated OR simulation OR device OR laptop OR web-based OR web based) AND (effect OR effects OR impact OR influence OR learning OR academic OR performance OR success OR outcomes OR effectiveness OR achievement OR efficacy) AND (learner OR student) AND (random OR randomized OR randomised) NOT review NOT protocol NOT meta-analysis NOT self-efficacy NOT self-reported))."

Reference lists of prior meta-analyses and systematic reviews were also inspected to locate additional appropriate records. Two authors independently filtered the publications first by title, then by abstract, and finally by full text. Differing opinions on the eligibility of a paper were deliberated with the third reviewer until a consensus was achieved. The final corpus was approved in early January 2024.

2.3. Data coding and synthesis

Two raters independently coded each primary study against the following characteristics: digital learning design, effect size data (means and standard deviation at the posttest and number of participants), and six hypothesized modifiers of digital learning effects, namely cognitive engagement mode (active vs. passive), sample size (<100 vs. ≥100), intervention duration (<8 weeks vs. ≥8 weeks), intervention setting (school vs. tertiary), domain subject (health sciences vs. other disciplines), and tool usage environment (controlled vs. ubiquitous). Given that the intervention duration is not reported [15], we contacted the corresponding author who filled us in on this detail. In instances where a paper presented multiple pertinent outcomes, they were averaged into one to prevent interdependence [16]. Hedge's g was computed as the effect size reflecting the difference between digital and non-digital conditions at the posttest. Individual Hedge's g values were then pooled within a random-effects model to obtain an overall Hedge's g while controlling for both within-study and between-study variances. The meta-analysis was completed using meta package in R. Separate and total differential effect sizes were visualized using a forest plot. Since all potential moderators were binary, a subgroup analysis was conducted for each variable to assess the statistical significance of differences among subgroup means. A subgroup had to comprise at least five cases as commonly recommended [17]. The I^2 index was computed to obtain estimates of the amount of between-study heterogeneity.

3. RESULTS AND DISCUSSION

3.1. Screening results

The literature search and selection algorithm yielded 17 eligible studies, as shown in Figure 1 involving a total of 1,896 individuals, with sample size range 26-204. A general overview of the included records can be consulted in Table 1, which shows that the overall timeframe considered was from 2015 to 2023, with 59% of the research reports being published between 2020 and 2023. This highlights that this meta-analysis is offering the latest information on the efficacy of educational digital tools.

3.2. Overall effect (RQ1)

The pooled data revealed that, when compared to no technology enhanced conditions, the overall effect size for e-learning interventions on cognitive domain outcomes was positive and moderate (g=.62, [95% CI:.38, .86], p<.01). The I^2 statistic implies that 83% of the variability in observed effects could be attributed to genuine differences between studies rather than sampling errors within individual studies. These results are summarized in the forest plot as presented in Figure 2, in which light green squares correspond to individual effect sizes whereas the black rhombus denotes the weighted average effect of all 17 interventions.

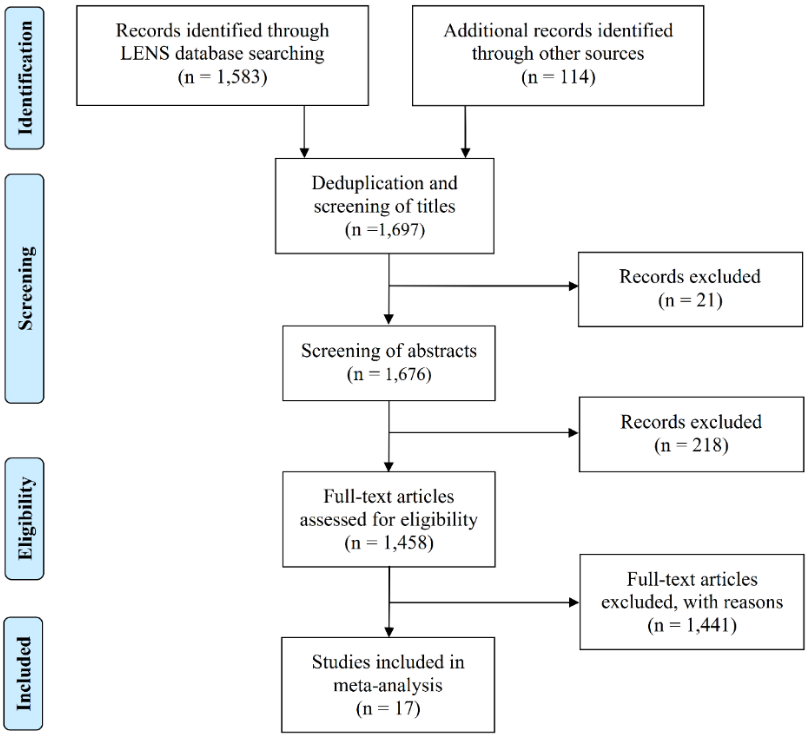


Figure 1. Flow diagram displaying database screening procedures

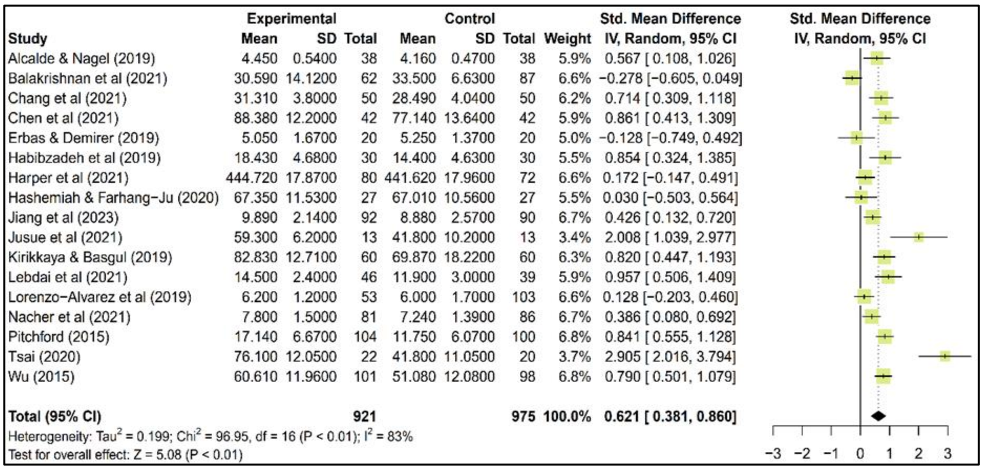
Table 1. Characteristics of studies included in this meta-analysis

Study	Intervention	Setting	N	Duration	Primary outcome
[18]	Online quizzes	Undergraduate	76	16 weeks	Final grade in an applied Algebra course
[19]	Web-based e-learning	Graduate	149	8 weeks	Pharmacy-related knowledge
[20]	Virtual mobile learning app	Undergraduate	100	5 months	Nursing-related knowledge and skills
[15]	Educational VR app with HMDs	Secondary	84	18 weeks	English L2 vocabulary
[21]	AR activities	Secondary	40	5 weeks	Biology-related knowledge
[22]	Online learning platform	Undergraduate	60	3 weeks	Cardiac dysrhythmia-related knowledge
[23]	English learning software	Middle	152	22 weeks	English L1 literacy
[24]	Learning English in Skype	Undergraduate	54	12 weeks	English L2 vocabulary and translation skills
[25]	Electrocardiogram online course	Undergraduate	182	4 weeks	Electrocardiogram-related knowledge and interpretation skills
[26]	Online course with practical activities	Undergraduate	26	6 weeks	Radiology images ordering and interpretation skills
[27]	Educational AR apps	Middle	120	6 weeks	Space and universe-related knowledge
[28]	VR patient simulator	Undergraduate	85	6 weeks	Urology-related knowledge
[29]	Virtual workshops	Undergraduate	156	4 weeks	Abdominal radiography-related knowledge
[30]	Web-based learning software	Undergraduate	167	4 months	Final exam score in the Psychology of memory subject
[31]	Math learning apps on tablets	Primary	204	8 weeks	Math-related knowledge
[32]	AR activities	Primary	42	4 weeks	English L2 vocabulary
[33]	English learning mobile app	Undergraduate	199	1 semester	English L2 vocabulary

3.3. Subgroup analyses (RQ2)

A random-effects-based subgroup analysis was conducted in an attempt to explain the inconsistent effects in the included publications. As per the interactive, constructive, active, and passive (ICAP) framework, technology-informed learning falls into four types: passive learning involves focusing on presented information without active interaction; in active learning, students physically engage with materials but do not generate new content; constructive learning sees students developing ideas beyond presented material or solving problems using it; finally, interactive learning implies constructive activities alongside collaboration with peers in engendering ideas or problem-solving [34], [35]. Initially, the intention was to categorize interventions based on the four types of digital learning modalities outlined in the ICAP framework. Yet, neither constructive nor interactive learning modality was the case for any of the included studies. Consequently, they were grouped into either passive or active cognitive engagement modes for analysis. It emerged from the subgroup analysis that interventions utilizing an active mode of cognitive engagement produced almost three times higher academic gain (g=.94, [95% CI:.30, 1.58]) when compared to passive ones (g=.36, [95% CI:.0, .72]) as shown in Figure 3. This evidence is partially in accord with the findings from a meta-analysis [36] in which activities such as watching videos coupled with completing quizzes rendered greater learning performance relative to more passive activities like online lectures. Nonetheless, the differences in Kapur *et al*. [36] were not subjected to inferential statistics, and the CIs for the effect size estimates are wide (as well as herein), while in the present meta-analysis, the difference was statistically insignificant (p=.07), so the issue of the efficacy of one approach or the other remains equivocal for now. Perhaps the matter does not require a verdict since, although active learning tends to afford students a better grasp of target concepts, passive learning is a mandatory step preceding active learning [37].

As regards intervention settings, digital learning among school students (g=.87, [95% CI:-.19, 1.93]) exerted a stronger mean effect, although not statistically significant (p=.44) in comparison to higher education contexts (g=.53, [95% CI:.18, .88]), as presented in Figure 4. This finding aligns to some extent with the results of a meta-analysis on technology-supported vocabulary learning [38], where a subset of individuals enrolled in secondary education outperformed college students. One possible explanation for such variance is that school students may benefit more from the interactive and engaging features of digital learning tools, which can enhance their learning motivation and attention [39]. Higher education students, on the other hand, may have more prior knowledge and experience with the subject matter, which may reduce the need for digital scaffolding and support [40].



Note: SD=standard deviation, SMD=standardized mean difference, CI=confidence interval

Figure 2. Forest plot of continuous outcomes

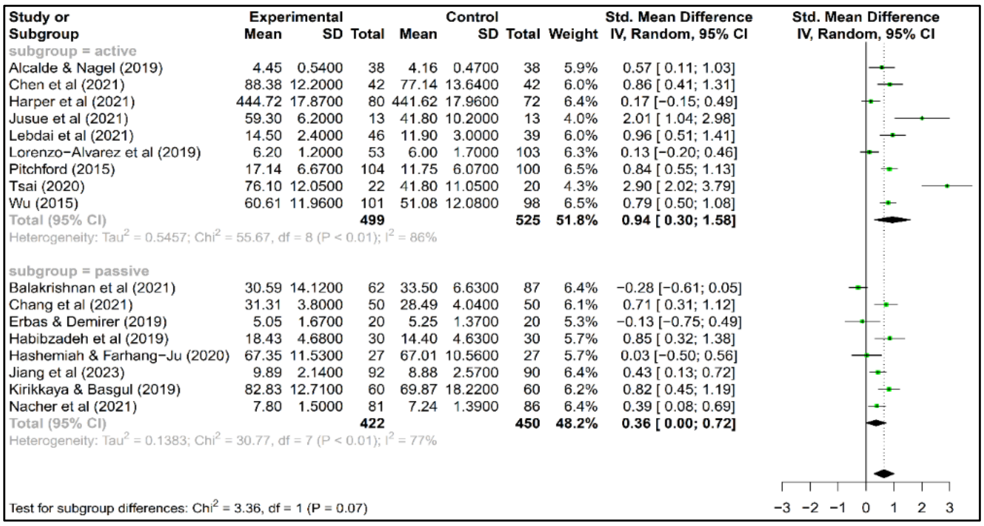


Figure 3. Subgroup analysis: cognitive engagement mode

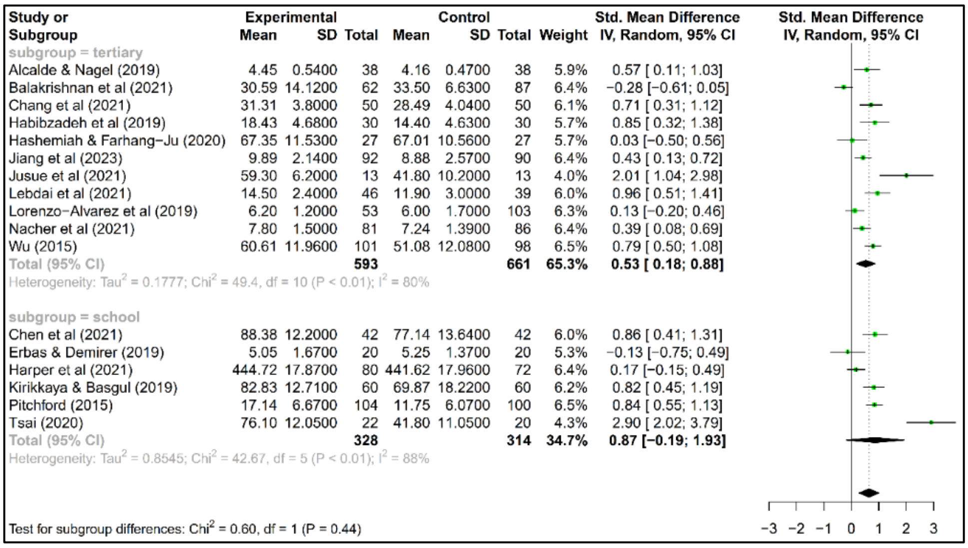


Figure 4. Subgroup analysis: intervention setting

Two-fold larger learning outcomes were observed for studies that enrolled less than 100 participants (g=.95, [95% CI:.14, 1.77]) as opposed to samples of 100 and more (g=.44, [95% CI:.15, .74]), as presented in Figure 5. The difference was not statistically detectable (p=.16). This finding is somewhat in keeping with a meta-analysis dedicated to digitized learning in high school math and science [10], in which the effect size was .59 for publications with samples over 100 subjects and .72 for those of 100 or fewer. In this respect, Slavin and Smith [41] emphasized that larger sample sizes in published literature are commonly linked to lower estimated effect sizes given that if the difference between two groups is substantial, a smaller number of observations is required to be confident that the difference is not due to chance. Moreover, reporting statistically significant findings is often an unstated condition for publication. Consequently, small sample studies with highly positive effects tend to be overrepresented in quantitative syntheses.

Interventions under eight weeks in duration ended up in learning achievement twice as high (g=.84, [95% CI:.23, 1.45]) as those lasting eight weeks and above (g=.43, [95% CI:.01, .85]) as shown in Figure 6. Nevertheless, this difference was not significant (p=.20). These results are consonant with prior integrative research [9]–[11], [42]. A typical explanation for this pattern is a novelty effect, which is mentioned in about every writing on technology in education. Discussing learning success elevated in short-term experiments over longer-term conditions, countless papers have attributed this to a flurry of interest that intensified engagement and processing of learning materials, but worn off over time, translating into habituation or even fatigue, with a drop in enthusiasm and academic performance [43]–[46]. While the novelty effect argument may have been viable in the 2000s or in the case of brand-new groundbreaking technologies, the technologies employed in the interventions analyzed here-including VR helmets-were unlikely to be perceived as something astounding for students in the mid-2010s, let alone the early 2020s. Therefore, even aside from the high heterogeneity of the estimates, it would hardly be reasonable to recommend short duration interventions or the integration of short-term digital activities into teaching-learning practices, considering the results presented in this meta-analysis. This is especially true because such activities might not align with the demands of regular classroom practices, which often extend over several months and involve rather complex skills or methods that cannot be accommodated within diminutive programs, so that longer schemes may be needed to ensure the effectiveness of e-learning [47].

Concerning subjects covered in the meta-analyzed studies, the total effect size found for those related to health sciences (g=.60, [95% CI:-.01, 1.22]) was on a par with investigations where other knowledge fields were learned (g=.68, [95% CI:.13, 1.23]), as presented in Figure 7. The difference between these subgroups was statistically indiscernible (p=.83). This finding humbly suggests that e-learning is effective across different domain subjects and that its specific content does not have a significant impact on quantitative cognitive outcomes. This is in line with the idea that, given the complex nature of teaching and learning, the interaction between educators and students, as well as the quality of learning resources and tasks, are more critical components than the format or subject matter in terms of academic attainment [48].

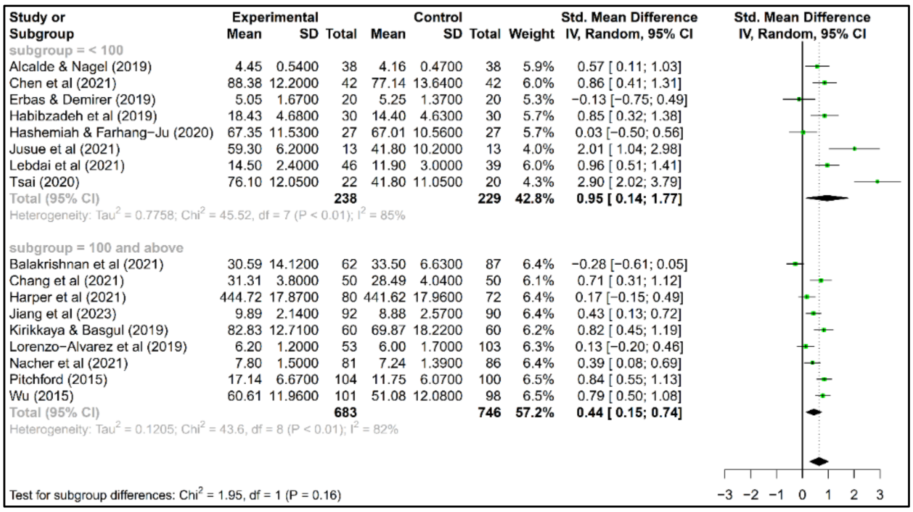


Figure 5. Subgroup analysis: sample size

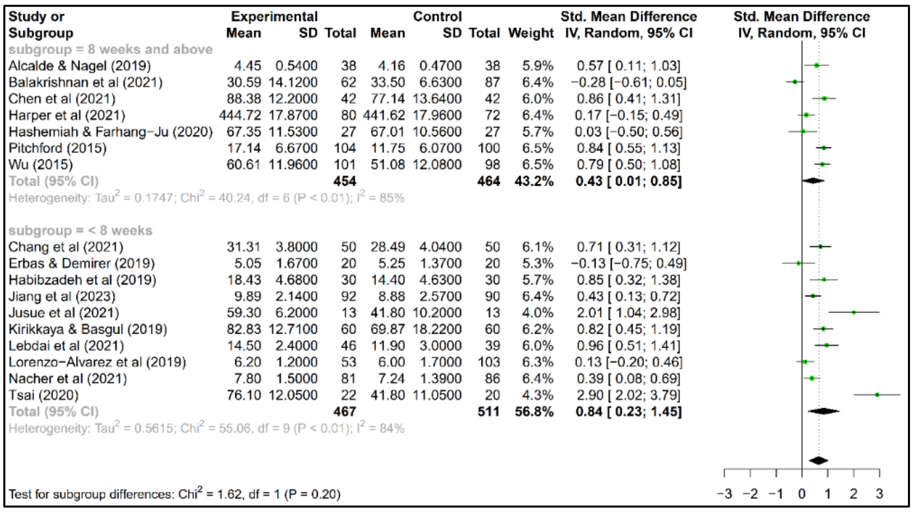


Figure 6. Subgroup analysis: study duration

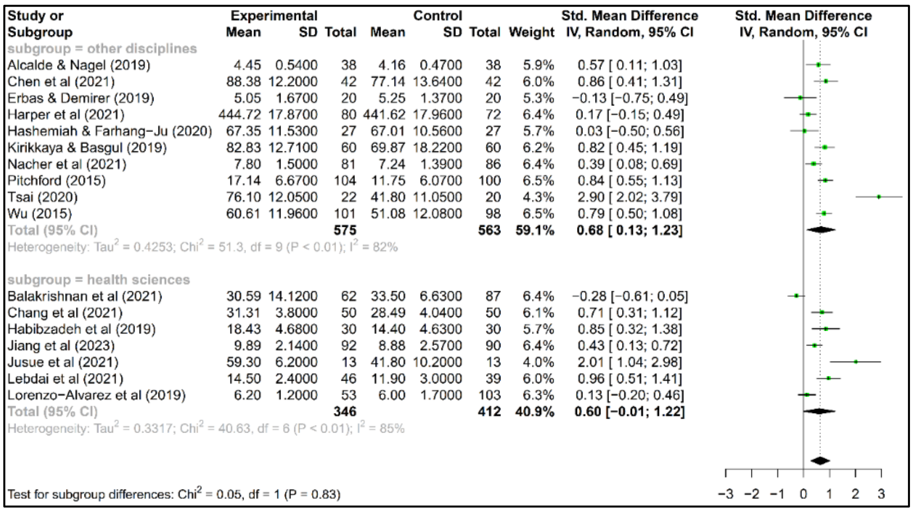


Figure 7. Subgroup analysis: domain subject

Regarding implementation setting, cognitive gains derived from studies in which the experimental digital tool was manipulated under the supervision of educators/experimenters (g=.99, [95% CI:-.35, 2.33]) was twice that of the subgroup where participants engaged in suggested procedures at a time and place convenient to them (g=.48, [95% CI:.07, .89]), as shown in Figure 8. However, there was a large uncertainty in effect sizes and the difference was insignificant (p=.32). This evidence does not corroborate the results of a meta-analysis [47], in which informal and unrestricted usage of mobile devices resulted in greater effect sizes when compared to formal research settings. Moreover, study by Hao *et al.* [38] discovered that technology-enhanced vocabulary learning in a self-paced uncontrolled manner tended to be more efficient than classroom-based activities.

One possible explanation for our finding is that different types of e-learning may require different levels of guidance. Alternatively, some digital learning conditions may be more enthralling or motivating than others, and thus foster more self-regulation and autonomy. From a theoretical lens, this outcome may be explained by the socio-cultural theory proposed by Vygotsky, emphasizing the importance of social interaction and guidance in the learning process. In controlled settings, the presence of conductors could provide scaffolding, support, and real-time feedback, facilitating a more effective cognitive engagement with the method. The structured nature of the expert-handled environment may shape a promotive learning atmosphere, potentially accelerating academic performance. Contrastingly, the subgroup of participants accomplishing their tasks ubiquitously may lack the social and instructional support provided in a classroom, laboratory or clinic, leading to smaller productiveness.

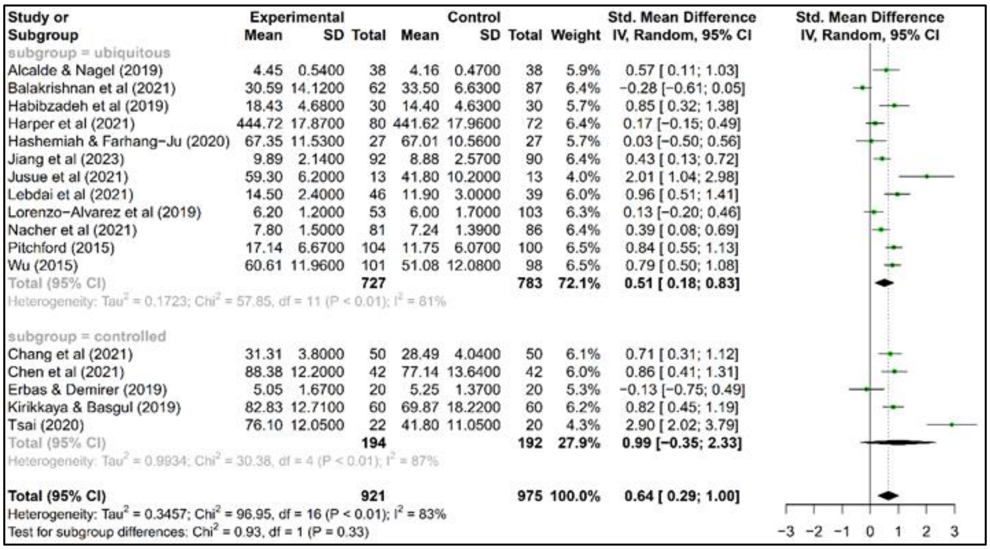


Figure 8. Subgroup analysis: tool usage environment

3.4. Publication bias

Since the set of effect sizes and all subgroups were heterogeneous, publication bias analysis could not be informative. However, to obtain a summary effect size adjusted to potentially unpublished documents, it was decided to generate a trim-and-fill funnel plot depicting the association between effect size and standard deviation using Meta-Essentials [49]. The funnel plot, as presented in Figure 9 detected one imputed point resulting in an adjusted combined Hedge's g of .49 (95% CI: .40, .59).

3.5. Implications and limitations

The results of this integrative work signify that students nearly equally benefited from technology-driven learning irrespective of domain subject, group sizes, experiment length, cognitive engagement modes, implementation settings, and tool usage environments. Substantial variability was the case for all subgroups and no significant differences between them were observed, inferring there may be other individual differences and contextual factors that could not be measured by experimenters or were overlooked herein. Thus, the present research, as well as previous meta-analytic studies, does not offer explicit evidence on the topic in question. Yet, the large effect size differences provide a basis for further exploration.

This paper aggregates fewer studies as compared to past meta-analyses due to our stricter eligibility criteria concerning research design and measurements. Expanding the timeframe to, say, 2000-2023 would not noticeably increase the list of primary studies to circumvent inter-study heterogeneity. The number of adequate publications in the first decade of the 21st century was low, as can be ascertained by examining the papers included in the meta-analyses of the 2010s [50]–[53], while contaminating a meta-analytic corpus with dubious evidence would be a moot option. One thing to keep in mind is that this limitation of the current meta-analysis mirrors the state of the art in the research field, spotlighting that the latter is in fact not even ready so far to unambiguously answer the first-generation question of whether digital learning is effective. Not to mention a shift to the second-generation question inquiring about conditions under which digital learning is more effective and the third-generation question on what mechanisms and mediators underlie digital learning efficacy.

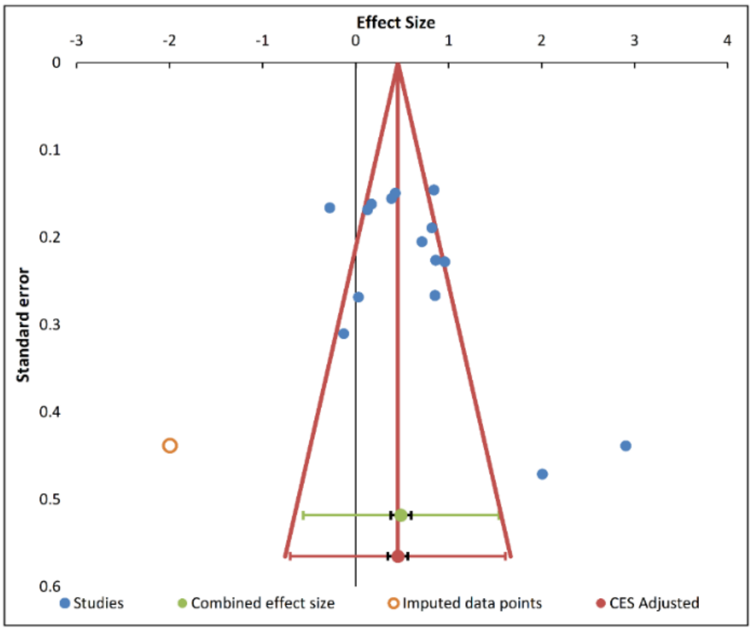


Figure 9. Publication bias funnel plot of standard error by Hedge's g

4. CONCLUSION

The findings have unearthed that, in comparison to traditional approaches, digital learning has the potential to be instrumental in improving outcomes in the cognitive domain. However, the high level of heterogeneity between studies introduces uncertainty, making it premature to draw definitive conclusions. As demonstrated by this study, there is a scarcity of controlled pretest-posttest studies with participants randomly assigned to groups in the field of e-learning. One might expect hundreds of such studies to have been published over all these years of the technological boom. This informs a priority for performing much more methodologically rigorous trials assessing the efficacy of technology-informed learning on objective cognitive outcomes in the coming years. This approach would allow for a more straightforward determination of e-learning efficacy and might even unravel the complex interplay of contextual variables and instructional strategies in digital learning environments, provided that future studies cover as many knowledge areas as possible in order to enable moderator analyses. Widespread use of more complex measurements than fill-in tests could be helpful in isolating the format effect from other factors. Given current trends, a promising direction appears to be the hybrid application of already well-known technologies with AI-assisted solutions in learning-teaching interventions.

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BIOGRAPHIES OF AUTHORS

Aizhan Koishybekova holds Master's degree in Education. She is a Ph.D. Candidate. Her research interests lie in computer science and mathematics education. She can be contacted at email: aizhankym@inbox.ru.

Nazym Zhanatbekova is a Candidate of Sciences in Education. She is currently the director of the Institute of Continuing Education at the Zhetysu University named after I. Zhansugurov. Her research interests include mathematics and physics education. She can be contacted at email: zhanatbekova@post.com.

Yerlan Khaimuldanov is a Ph.D. in Mathematics. His research interests focus on mathematics education. He can be contacted at email: khaimuldanov_e@mail.ru.

Assel Orazbayeva holds Master's degree in Education. She is a Senior Lecturer at the Zhetysu University named after I. Zhansugurov. Her research interests include computer science and mathematics education. She can be contacted at email: asel.orazbaeva@mail.ru.

Dariya Abykenova is a Ph.D. in Psychology and Education. Her major research interest is information and communication technology. She can be contacted at email: abykenovad@pspu.kz.