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Harnessing AI-based learning media in education: A meta-analysis of its effects on student achievement

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From the most straightforward kind of technology—audiovisual learning—to the application of artificial intelligence in education, technology has been used in education for over 20 years. Despite the growing popularity of AI-based learning media technology, there is still a dearth of reliable empirical data about its effects on student achievements. This meta-analysis aims to investigate the impact of intervention time and combine findings from several studies to paint a more comprehensive picture of the usefulness of AI media in education. In this study, a meta-analysis design is employed in quantitative research. The Publish or Perish tool gathered secondary data from published papers using the Scopus database and Google Scholar—data analysis for group contrast meta-analysis data using the R software. The study's findings demonstrate how using AI-based learning resources greatly impacts students' academic performance. P value total effect size and three moderator variables (continent, gained achievement, and intervention duration < 0.05) show that the aggregate value of the summary effect in AI-based learning media, which integrates technology products with software, web programs, augmented reality, and gamification in increasing student achievement from elementary school to tertiary level from 2019 to 2024, is still providing significant influence. Thus, artificial intelligence (AI) should be used more extensively in preparing learning media to maximize students' academic and non-academic successes.

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Introduction

Technology has been increasingly developing and experiencing evolution since it was first used in education, especially as a learning tool. The evolution of technology implementation in the world of education began at an early stage in 1920 – 1930. It is also now becoming more sophisticated with the presence of Artificial Intelligence (henceforth AI) as a form of technology implementation in the world of education (del Campo et al., 2012), especially in teaching methods and learning environments (Nethra R MBA, 2019; Velayutham et al., 2022).

Technology has constantly improved access to education, from historical inventions like the printing press to contemporary digital technologies (Li, 2023), solved physical barriers to online learning (Hassan, 2023), personalized learning experiences include augmented reality (AR), virtual reality (VR), and AI (Hassan, 2023), never-before-seen opportunities thanks to digital assistance aids for disabilities (Timmers, 2018). These demonstrate that advancements in technology and existence are essential and impact education, not just during the learning process but also during the planning and assessment stages.

On the other hand, technology has also made it easier for students to access research tools and learning resources, allowing teachers to present more engaging classes to their pupils (Nethra R MBA, 2019). Through platforms like Zoom and Google Meet, students may now collaborate and communicate with each other more easily (Velayutham et al., 2022), more accessible to people in rural places to access online resources and chances for higher education (Kiong, 2022), improving both the efficiency and enjoyment of teaching and learning (Raja & Nagasubramani, 2018), and has improved education by giving students more opportunities for studying, more individualized learning experiences, and more control over their education (Kiong, 2022). Using technology in the teaching and learning process benefits both students and teachers.

Integrating technology into education aims to establish settings that support self-directed learning, communication, and teamwork while equipping students for success in an increasingly digital world (Abass & Abas, 2019; Kalyani, 2024). That research concludes that conducting classrooms with technology assistance, especially AI in the learning media, influences students' academic and non-academic performance.

At all educational levels, artificial intelligence (AI) has demonstrated beneficial effects on students' academic performance. AI tools facilitate collaborative settings, offer instant feedback, and improve individualized learning experiences (Kaledio et al., 2024). Research shows that artificial intelligence (AI) can successfully address particular learning demands, enhance attitudes toward learning, and increase motivation for study habits (Chiu et al., 2023; Hooda et al., 2022). According to a meta-analysis, grade levels and the subjects covered in mathematics classes were important mediators of the tiny but substantial effect size of AI on primary pupils' mathematical achievement (Hwang, 2022). The beneficial effects of AI and computational sciences on student performance, especially in STEM fields, were confirmed by another systematic review and meta-analysis (García-Martínez, 2023). However, privacy issues and the dangers of relying too much on AI technologies must be addressed (Kaledio et al., 2024). AI can potentially improve students' academic performance; however, cautious use and more study are required.

The influence of AI in the learning process can be stuck with the learning media used by teachers and students. By leveraging input variables like attention, meditation, and cognitive workload, AI-based models can predict individual learning styles and personalize learning experiences (Lokare & Jadhav, 2024). By using concept mapping and self-evaluation, these models can also help teach programming principles (Huddar & Kharade, 2023). Adaptive learning support systems can be designed with the help of AI technologies in education, which include supervised learning, mining techniques, and Bayesian methods (Song, 2024). Moreover, cloud computing and database management systems can combine AI-based learning models to effectively handle and distribute massive volumes of educational data (Dhaya et al., 2022). AI-based learning models present exciting opportunities to revive education by giving pupils individualized, efficient, and data-driven learning experiences through AI-based learning media. Though AI-based learning media is in the learning process, it can influence learning achievements.

Meta-analyses were carried out to gather more conclusive data on the impact of AI-based learning materials on student accomplishment. The goal is to look at more publications that do not start with how AI is used in education and then analyze how employing AI-based learning materials affects student achievement. This meta-analysis research aims to demonstrate how applying AI-based learning materials affects student accomplishment in several earlier studies and what moderator variables come into play if the results have a significant impact.

Method

Design

This research uses a quantitative research model with a meta-analysis design. The objective of this study is to identify how significant the average influence of AI-based learning models is in improving students' academic and non-academic achievements, starting from primary, secondary, and tertiary levels. Meta-analysis research provides an alternative to dig deeper into the average influence of AI-based learning models in improving students' academic and non-academic achievements, starting from primary, secondary, and tertiary levels, by evaluating previous research findings with statistics.

The procedures for conducting a meta-analysis are discussed by Retnawati et al. (2018). When conducting a meta-analysis that employs study parameters in the form of means, researchers must consider whether each study measures variables on the same scale. The standard error of the effect size for the same size across studies and formulas. This study's meta-analysis utilizes artefacts or studies on variables with the same scale. The effect size—the average score of certain variables that are the focus of each study—is taken as the mean in this meta-analysis. Then, the variable moderators' influence on the effect size matter will be analyzed before reporting the meta-analysis result.

Going deeper, this meta-analysis research design uses articles from the results of experimental studies, either purely experimental or quasi-experimental. The articles used in this analysis include the number of samples, mean values , and standard deviations for each experimental and control group from the post-test after treatment involving Artificial Intelligence in the learning model.

The research data in this study are articles accessed and downloaded from the Publish or Perish computer program with sources from the Scopus and Google Scholar databases. These two sources can provide references for the required themes. These two sources help researchers to retrieve and analyze relevant studies thoroughly and concisely. These two sources provide a systemic way to conduct a literature review. From Google Scholar and Scopus Search, Publish, or Perish was chosen as a filter because researchers can fully access these two sources. All studies relevant to using AI-based learning models in improving academic and non-academic achievement were downloaded and analyzed further. The span of a decade is not limited to the last few years. This is because the emergence of AI in education, especially its integration into learning models, mushroomed during the pandemic around 2019. So, the topic itself is new and has quite a significant gap in research.

Data Collection and Analysis

In this meta-analysis study, the SALSA framework assists the data collection and analysis process until the results are found. The SALSA Framework has four sequential steps: Search, Assessment, Synthesis, and Analysis (Mengist & Soromessa, 2020; Vicente-Sáez & Martínez-Fuentes, 2018). This framework aims to improve the selection of data used. Figure 1 shows the steps for collecting data using the SALSA framework.

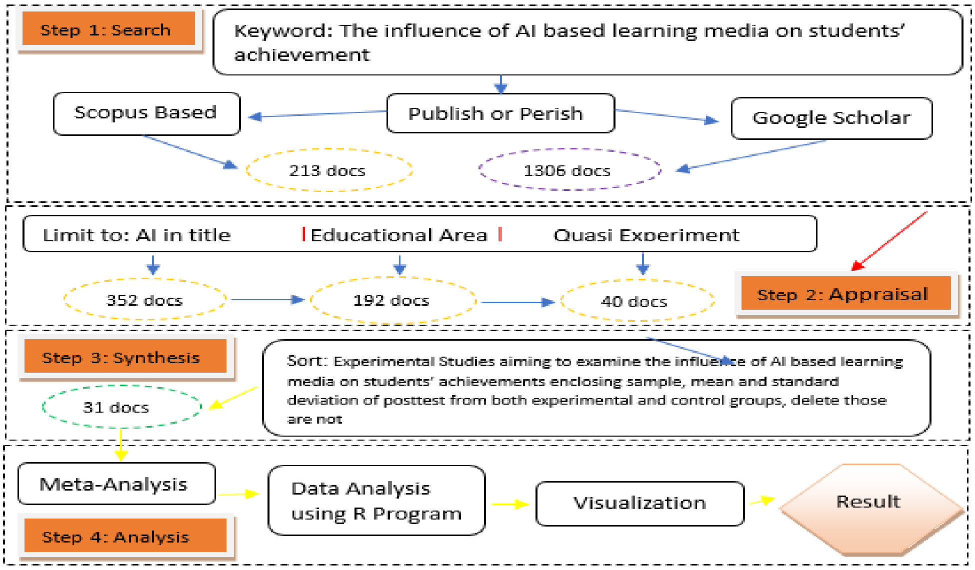

Figure 1. SALSA Framework

Figure 1 depicts the steps for collecting and analyzing data to achieve meta-analysis results using the SALSA framework. The SALSA framework achieves research objectives and reduces data collection and analysis bias. It starts with the first step, namely, search. After determining the data sources that can be used to collect articles related to the meta-analysis theme, the following process is searching and downloading articles that match the theme. The search keyword used the keyword "The influence of AI-based learning media on achievement and AI on students' achievement."

From the search for articles from the Scopus Database, 213 articles were obtained, and from the Google Scholar database using Publish and Perish software (Harzing, 2007), there were 1302 articles. The second RIS file containing the articles' metadata was collected and sorted by title. Looking at the article's title that mentions AI, from 1515 articles, it has decreased drastically to 352 articles. Furthermore, filtering in terms of fields, namely education, was carried out and resulted in 192 articles. The final stage was selecting articles that discussed the influence of AI-based learning media on the world of education using quasi-experimental research methods, leaving 40 documents. This stage is included in the Appraisal phase.

In detail, synthesizing the articles according to the themes collected is the third step, namely synthesis. This third step is done manually. A total of 40 articles discussing the influence of AI-based learning media on student achievement were synthesized one by one by paying attention to several important pieces of information. Important information that must be contained in the articles that will ultimately be analyzed are articles that accommodate experimental research (pure/quasi), research subjects who are students, at any level, involve the use of AI-based learning media in the implementation of the treatment, the final ability measured is part of student achievement, both academic and non-academic, each article reports information on the number of samples involved, the mean and standard deviation of each group (experimental group and control group) obtained from tests carried out after the treatment was carried out (post-test). From the synthesis process carried out manually, 31 articles were finally obtained from journals, book chapters, books, and seminar proceedings ready for meta-analysis.

31 studies were analyzed in this research. All research articles have been filtered according to meta-analysis requirements. You can be sure that all articles have the same detailed information. Each article uses an experimental design in data collection, making AI-based learning media the treatment given to the experimental group and reporting the information needed during the analysis process. The selection process results obtained 31 articles whose studies started at the elementary school level and went to the university level. All research articles aim to increase student achievement by using AI assistance to compile learning materials, have an experimental implementation duration of 3-12 weeks, and come from various Asian countries. This is possible because AI-based learning media in Asia is still not as familiar and widely and continuously applied in learning. This is different from developed countries, which already live side by side with sophisticated technology. Therefore, studies regarding the influence of AI-based learning media on student achievement need to be explored again. Moreover, the condition of education in most developing countries is experiencing learning losses due to the impact of the pandemic.

The fourth step is analysis. The final result was 31 articles that were suitable to continue with the analysis process and then carry out meta-analysis by manually recording the information needed to finally carry out meta-analysis with the help of the "meta" and "metaphor" packages in the R Studio computer program (RStudio_Team, 2020). Detailed information collected from each article is the identity of the author, year of publication, number of samples (N), mean ($\bar{X}$), and standard deviation (s) for each experimental (E) and control (C) group. Other detailed information related to moderator variables is the country, year of implementation, type of AI used, experimental research objectives, education level, and duration of treatment (experimental group), as shown in Appendix 1. Table 1 presents the results of the meta-analysis of the selected articles.

Table 1. *Detailed Article Selection Results for Meta-Analysis of Selected Articles*

Study	Authors	NE	$\bar{X}$ E	sE	NC	$\bar{X}$C	sC
1	(Huang et al., 2023)a	43	55.00	19.76	59	50.69	23.00
2	(Huang et al., 2023)b	9	3.88	20.17	10	14.70	29.39
3	(Huang et al., 2023)c	20	18.20	18.72	28	4.14	20.30
4	(Huang et al., 2023)d	14	10.14	21.51	21	11.85	22.48
5	(Liu et al., 2022)a	45	3.99	0.78	23	3.59	1.04

6	(Liu et al., 2022)b	45	3.76	0.96	23	3.60	1.02
7	(Liu et al., 2022)c	45	3.67	0.92	23	3.47	0.97
8	(Liu et al., 2022)d	45	3.74	0.90	23	3.61	1.20
9	(Liu et al., 2022)e	41	4.13	0.82	21	4.03	0.68
10	(Liu et al., 2022)f	41	3.29	1.04	21	3.34	1.11
11	(Liu et al., 2022)g	41	3.65	1.09	21	3.52	1.09
12	(Liu et al., 2022)h	41	3.87	1.13	21	3.61	1.10
13	(Liu et al., 2022)i	41	3.74	0.79	21	3.63	0.81
14	(Das et al., 2023)j	50	72.80	7.30	50	64.70	7.40
15	(Junaidi, 2020)	32	69.59	7.86	30	63.61	5.57
16	(Wu & Wang, 2021)	15	14.30	3.18	16	11.40	4.78
17	(Topal et al., 2021)	20	21.25	0.28	21	20.48	0.28
18	(Simanungkalit et al., 2024)a	24	7.90	1.34	28	7.03	1.55
19	(Simanungkalit et al., 2024)b	24	101.63	4.20	28	96.18	4.80
20	(Dai et al., 2024)	39	47.74	93.08	38	30.03	93.08
21	(Wei, 2023)a	30	73.86	15.26	30	61.11	14.97
22	(Wei, 2023)b	30	3.89	1.80	30	3.35	1.50
23	(Wei, 2023)c	30	3.94	0.73	30	3.37	0.76
24	(Samra, 2021)a	30	32.40	2.40	30	26.40	4.80
25	(Samra, 2021)b	30	20.63	6.30	30	20.10	5.90
26	(Samra, 2021)c	30	5.31	2.43	30	5.55	2.49
27	(Younes, 2021)a	34	28.74	4.72	34	14.21	3.48
28	(Younes, 2021)b	34	27.24	8.83	34	29.12	7.08
29	(Younes, 2021)c	34	34.55	2.42	34	28.73	3.41
30	(Alomari, 2020)	17	20.80	2.90	17	20.40	2.30
31	(Kanvaria & Suraj, 2024)	35	18.51	2.74	35	17.31	3.01

Note: The outcomes of the articles chosen for meta-analysis are compiled in this table. Multiple studies, categorized by author, number of samples (NE and NC), mean (XE and X̄C), and standard deviation (sE and sC) for both the experimental (E) and control (C) groups, are represented by each row. The letters a, b, and c after the author's name indicate the variance of achievement data presented in the articles.

The discrepancies in study findings about the impact of AI-based learning media on student accomplishment are explained in detail in Table 1. Significant differences were across the 31 papers gathered, including those regarding the study, participants, mean, and standard deviation for the experimental and control groups. Overall, table 1's data gives an overview of the impact numerous studies have found that the intervention under test—in this case, the employment of AI-based learning media—has on students' academic performance. The mean and standard deviation offer crucial details regarding the degree of variation seen in each study and the efficacy of the intervention in altering the outcomes under examination.

Findings and Discussion

The analysis results in this meta-analysis study can produce a treatment effect (estimated effect size), study heterogeneity, summary effect, and publication bias. Treatment effects can provide information regarding the estimated effect size of each study used.

Heterogeneity provides an overview of the distribution of studies. The summary effect will provide information regarding the influence produced by a treatment given to a skill. In this research, the use of AI-based learning media on student achievement. These results also show the effect of using AI in learning media on student achievement by considering several moderator variables such as country, the form of AI-based learning media, and the length of treatment (duration) used. Then, to strengthen these results, publication bias was also looked at using funnel plots and Egger tests.

Treatment Effect/Effect Size

Treatment effect (TE), which is usually also used as Effect Size (ES), can provide information regarding the differences between observed results between groups that receive specific treatment or interventions and control groups that do not receive treatment or intervention. Table 2 shows the results of this treatment effect.

Table 2. *Treatment effect*

Study	TE	SE	Study	TE	SE
Study1	0.19714	0.201004	Study17	2.696717	0.441837
Study2	-0.40574	0.4653	Study18	0.588042	0.284542
Study3	0.703323	0.302164	Study19	1.183926	0.303158
Study4	-0.07559	0.345165	Study20	0.188356	0.228471
Study5	0.451775	0.259401	Study21	0.832532	0.269865
Study6	0.161335	0.256716	Study22	0.321693	0.259974
Study7	0.211019	0.256996	Study23	0.755004	0.267831
Study8	0.12725	0.256567	Study24	1.56059	0.297176
Study9	0.127224	0.268604	Study25	0.08571	0.258325
Study10	-0.04641	0.26838	Study26	-0.09629	0.258358
Study11	0.117768	0.268567	Study27	3.464069	0.390132
Study12	0.229209	0.269184	Study28	-0.23223	0.243399
Study13	0.136331	0.268643	Study29	1.945924	0.297136
Study14	1.093556	0.21497	Study30	0.149217	0.343533
Study15	0.862097	0.266388	Study31	0.412314	0.241714
Study16	0.691104	0.371387			

Note: Treatment Effects (TE) and Standard Errors (SE) from the examined trials are compiled in this table. Treatment effects reveal how effective the intervention was; some studies, like Studies 17 and 27, had significant positive benefits, while other studies, like Studies 2 and 10, had adverse or almost negligible effects. Standard errors differ, which reflects variations in the accuracy of estimations between researchers. The significance of the consequences of the treatments under analysis is made more evident by this table.

Table 2 shows that the average treatment effect from each study is 0.595, with the average standard error being 0.288. This treatment effect shows that treatment or intervention using AI-based learning media has a positive impact. The positive impact of using AI-based learning media regarding the average effect shows a beneficial effect. Meanwhile, the resulting standard error indicates uncertainty in estimating the treatment effect. The greater the mean standard error value, the greater the uncertainty in estimating the treatment effect. A relatively high standard error value indicates a significant uncertainty when estimating a given treatment's effect.

Heterogeneity Test

This heterogeneity can be seen in variations or differences between the studies included in the analysis. Heterogeneity describes the degree of dissimilarity between study results that may be due to differences in study characteristics, populations, research designs, or other relevant factors (Stogiannis et al., 2024). The result of the Heterogeneity test is displayed in Table 3.

Table 3. *The Test Result of Heterogeneity*

Heterogeneity Quantification			
tau^2	I^2	tau	H
0.5312 [0.3243; 1.1423]	83.5% [77.5%; 87.9%]	0.7288 [0.5695; 1.0688]	2.46 [2.11; 2.88]
Heterogeneity Test			
Q	d.f.		p-value
182.03	30		< 0.0001

Note: The analyzed studies exhibit significant heterogeneity, as the table shows. Most of the variation between studies is due to real heterogeneity rather than random error, as indicated by the tau² value of 0.5312 and I² of 83.5%. Additionally, the H value of 2.46 supports the existence of significant heterogeneity. With a p-value of less than 0.0001, the Q heterogeneity test yielded a value of 182.03, indicating that the variation observed amongst the studies was substantial and not coincidental.

Table 3 exhibits the result of the Heterogeneity test. The Q test determines if study results vary more than chance would predict. Significant heterogeneity exists when the p-value is extremely low (< 0.0001). The heterogeneity results show that the data used is quite heterogeneous. Each study used this data, which is quite varied, with a proportion of 83.5%. So, the studies used in this research are quite heterogeneous regarding study characteristics. These findings suggest that the papers included in this meta-analysis exhibit substantial and high heterogeneity. The Q test's high I^2 value (83.5%) and extremely low p-value (< 0.0001) support the idea that additional variables that vary throughout studies also contribute to variation in results.

Stogiannis et al., (2024) claim that the high heterogeneity among the papers included in this meta-analysis indicates substantial diversity. This indicates that this approach can yield deep and thorough explanations and analyses. In addition, significant heterogeneity may serve as a motivator for additional subgroup or moderator variable analysis, potentially impacting these studies. Additionally, the outcomes of subsequent research may benefit from this high degree of result heterogeneity. High heterogeneity also indirectly supports the hypothesis that the random effect model is utilized to assess the summary effect.

Publication Bias Evaluation

Before starting the core analysis, summary effect, to see the significance of the influence of using AI-based learning media on student achievement resulting from the 31 articles that have been published, it is necessary to determine their quality. One way to determine this quality is to evaluate publication bias. Publication bias is an essential step in meta-analysis to identify and reduce the effects of bias that may affect the validity of the analysis results (Mathur & Vanderweele, 2020). Publication bias occurs when studies reported and published are more likely to report statistically significant results or results that support the researcher's hypothesis. In contrast, studies with negative or non-significant results are less likely to be reported or published. Publication bias in this research can be seen from the funnel plot and Egger test.

In meta-analyses, funnel plots are used to identify publication bias by showing the sample size or variation on the vertical axis and each study's effect size on the horizontal axis (Duval & Tweedie, 2000). The study points will be distributed symmetrically in a cone if there is no publishing bias; if there is, the graph will be asymmetric. Funnel plots, in which tiny studies with significant variances tend to be scattered more widely at the bottom of the graph, are also helpful in measuring study precision and identifying inhomogeneity between studies (Sterne & Egger, 2001). A funnel plot's asymmetry could indicate bias or other issues that need more research (Duval & Tweedie, 2000). Further, Mathur and Vanderweele (2020) explain that research that exhibits symmetry in the meta-analysis's funnel plot suggests that there may be no publication bias in the results, making them more legitimate and accurate. This symmetry boosts the meta-analysis's credibility since it shows more comprehensive and objective data without distorting the conclusions due to study selection bias. Furthermore, it suggests that measurable components rather than extraneous effects are more likely to cause variances in study results, enhancing the validity and dependability of the analysis's conclusions.

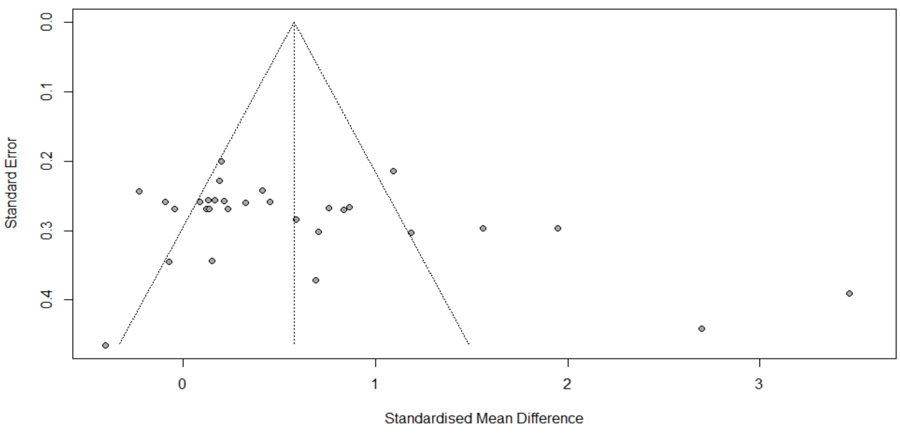

Figure 2. Funnel Plot

Figure 2 shows that the studies involved in this meta-analysis are divided asymmetrically. This concludes that biased publication is captured in this meta-analysis. This means that the results of this meta-analysis should be considered carefully (Duval & Tweedie, 2000; Mathur & Vanderweele, 2020; Sterne & Egger, 2001). The statistical results strengthen the decision on publication bias of the studies in this meta-analysis. These statistical results can be seen from the linear regression results of funnel plot asymmetry via the Egger test. The results of calculations using the Egger test are shown in Table 4.

Table 4. *The Test of Funnel Plot Asymmetry Using Linear Regression*

Test result			
t	df	p-value	Bias estimate
2.28	29	0.0298	5.5843 (SE = 2.4445)

Note: This table shows the results of linear regression tests to find asymmetry in funnel plots, which are used to spot possible publishing bias. The results demonstrate the statistical significance of the funnel plot's asymmetry with a t-value of 2.28, degrees of freedom (df) of 29, and a p-value of 0.0298. The analysis yielded a bias estimate of 5.5843, accompanied by a standard error (SE) of 2.4445, suggesting the potential for bias in the research's publications.

The findings of this research show that the funnel plot in your meta-analysis is imbalanced or asymmetric, which may be a sign of publication bias. Studies with unfavorable or inconsequential outcomes may be published less frequently than studies with favorable or significant results due to publication bias. A t-value of 2.28 indicates the degree of departure from perfect circumstances (no bias). The likelihood of asymmetry or bias increases with the t-value. Without publication bias, a p-value of 0.0298 suggests less than a 3% probability that the observed results result from pure chance. The results were deemed significant because the p-value was less than 0.05, indicating publication bias.

Then, standard error (SE) indicates the degree of certainty associated with the estimate, while bias estimates (5.5843) and SE (2.4445) offer a quantitative assessment of the potential bias's magnitude. The significance of the results suggests that the studies in your meta-analysis may be out of balance and that studies with non-significant or negative outcomes may be under-represented. Those results translate into an asymmetric funnel plot. This indicates that it is important to proceed cautiously when examining meta-analyses' results because they can be skewed by publication bias, which could inflate the stated effects.

However, publication bias does not make your meta-analysis "bad" but indicates that the results should be interpreted cautiously (Duval & Tweedie, 2000; Sterne & Egger, 2001). The quality of a meta-analysis depends more on how you recognize, report, and address these biases. On the other hand, this meta-analysis result cannot be generalized. It can only be implemented in the same context of research or treatments. A good meta-analysis is transparent about its limitations and takes steps to minimize the influence of publication bias on its conclusions.

A funnel plot analysis, like the one shown in Figure 2, can be used to reduce the effect of publication bias. Other strategies include analyzing the moderator variables to determine the impact of each factor and performing a fail-safe N calculation, which will be the next step (Borenstein, 2019; Borenstein et al., 2021; Higgins et al., 2003; Higgins & Green, 2011; Rosenthal, 1979; Sterne & Egger, 2001). Taking these actions can lessen the effects of publication bias and improve the validity of meta-analyses' findings.

Fail-safe N Calculation

In meta-analysis, fail-safe N is used to evaluate how resilient results are to publication bias, i.e., whether significant results can be sustained in the face of bias. It evaluates the likelihood of publication bias, counts the number of studies with null results required to turn a significant result into a nonsignificant one, and boosts confidence in the findings (Borenstein et al., 2021; Higgins et al., 2003; Rosenthal, 1979). The meta-analysis results are robust and stable when the Fail-safe N value is high; potential instability is indicated when the value is low. Fail-safe N further aids transparent result interpretation and presentation.

In conclusion, fail-safe N computations are a crucial tool in meta-analyses that assess how resistant findings are to publication bias. This makes it easier for readers and researchers to evaluate the meta-analysis's conclusions' stability and dependability despite the potential for unpublished studies or other forms of publication bias.

Table 6. *The Rosenthal Approach in Calculating Fail-safe N*

Observed Level of Significance	Target Level of Significance	Fail-safe N
<.0001	0.05	1302

Note: The results of Fail-safe N calculations using the Rosenthal method are shown in this table. This method determines the number of additional studies with non-significant findings required to lower the meta-analysis's overall significance. It took 1302 more studies with non-significant results to refute the overall significance of the meta-analysis results, given an observed significance level of <.0001 and a goal significance level of 0.05. This demonstrates how the meta-analysis's conclusions are incredibly solid and resistant to being swayed by unimportant side research.

The outcome of the Fail-safe N computation is shown in Table 6. The results of the investigation "Fail-safe N Calculation Using the Rosenthal Approach" shed light on how immune meta-analysis conclusions are to potential publication bias. Below is an explanation of these findings: p-value from a meta-analysis that indicates the results are highly statistically significant (p-value less than 0.0001) is called the "observed significance level," or <.0001. The conventional threshold for statistical significance is set at the target significance level (p-value = 0.05). The meta-analysis results are deemed significant if the p-value is less than 0.05. N: 1302, fail-safe: The quantity of supplementary research with null (non-significant) results needed to increase the p-value of your meta-analysis results to non-significant (more than 0.05) is known as fail-safe N. In this instance, 1,302 more trials with no effects would be required before the meta-analysis results would no longer be considered significant.

A high Fail-safe N number (1302) indicates that the meta-analysis findings are robust and resistant to the effects of publication bias. This implies that the aggregate results would still be significant even if the meta-analysis had excluded over a thousand additional papers with non-significant results. Because it is doubtful that so many studies with null results have yet to be published or discovered, the results appear resistant to potential publication bias. Overall, the findings of this meta-analysis are more reliable, albeit publication bias should always be addressed.

Summary Effect

The aggregate estimate of the effect size obtained from each of the individual studies that were part of the analysis is referred to as the "summary effect" in meta-analyses. Depending on the data being examined, this impact size may be a mean difference, odds ratio, risk ratio, or another effect size. When the results of multiple studies are combined, and the weight of each study is taken into consideration—often based on the sample size or accuracy of the study's findings—the summary effect is produced, which is a single figure that represents the overall effect of the intervention or relationship under study (Candra & Retnawati, 2020; Cooper et al., 2009; Etemadfar et al., 2020).

The first step toward computing the summary effect is selecting a model appropriate for examining the data. The heterogeneity test results and the analysis results from the test of choosing the best summary effect estimating model can be used to choose this model. The model appropriateness tests in a meta-analysis are calculated using the RStudio program. Table 5 displays the analysis findings for selecting the model for the summary effect analysis.

Table 5. *Meta-Analysis with Hedge's g Result*

SMD	95%-CI	z p-value
Model of Common Effects	0.4940 [0.3975; 0.5904]	10.04 < 0.0001
Model of Random Effects	0.5759 [0.2997; 0.8520]	4.09 < 0.0001

Note: The outcomes of a meta-analysis employing Hedge's g effect size are shown in this table. A substantial effect is shown by the Common effect model's standardized mean difference (SMD) value of 0.4940 with a 95% confidence interval [0.3975; 0.5904] and z value of 10.04 with a p-value < 0.0001. The Random effects model also indicates a substantial effect with increased inter-study variability, where the SMD is higher at 0.5759 with a 95% confidence interval [0.2997; 0.8520] and a z value of 4.09 with a p-value < 0.0001.

The model determination test calculation results are displayed in Table 5, which will be utilized to analyze the data results from the 31 articles that have been thoroughly examined. One of the two models—the Random Effects Model and the Common Effects Model—will be utilized to calculate the summary effect in this meta-analysis. The confidence interval value, represented by the number 0.5759 [0.2997; 0.8520], indicates the model that will be used to analyze the summary effect based on several detailed data points that were acquired. This indicates more significant heterogeneity between research when using a random effects model (Borenstein et al., 2021).

The summary effect is the combined treatment effect of the studies used. The summary shows the results of calculations using the random effect statistical method. This random effect considers variations or diversity between studies and factors that will influence the treatment in each study (Hansen et al., 2022).

The results of the analysis show that the use of AI-based learning media has a significant influence on student achievement. This result can be seen in the p-value, where the p-value is 0.00 < 0.05. This means that the use of technology, such as e-books, applications, the web, etc., has a real impact on improving literacy skills at an early stage. The effects of each study are shown in detail in Figure 3 of the forest plot.

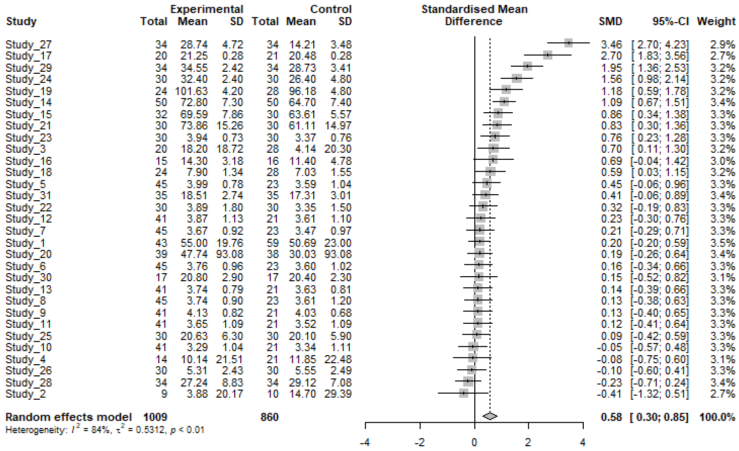

Figure 3. Forest plot

Next, the study's summary effect size should be investigated. The aggregate's summary or effect size can be seen from the forest plot. Forest plots contain various elements. In addition to the bars in the confidence interval plot of each study and their effectiveness, each bar in response to a specific meaning is also presented. The left end is the lower limit, and the right is the upper limit. In the middle, there is a box with a size indicating the amount of weighting and its position indicating the location of the effect size for each study. At the bottom is a Diamond whose area is the total weighted area of each study, and its position indicates the size of the aggregate effect size (Retnawati et al., 2018).

The forest plot results show that the distribution of effects is quite varied in each study. Every study points to the influence of AI-based learning material on students' achievement; some have positive and negative effects. However, most studies show positive effects. Moderate to negative effects were observed in about 5% of all studies. Apart from that, most of the weights or roles of each study are below 2% to influence the conclusions of the meta-analysis. However, researchers also looked at other variables that could have influenced the effect of implementing AI-based learning material on students' achievement.

Variable Moderators

The meta-analysis result for some variable moderators supports the effectiveness of utilizing AI-based learning media to enhance students' achievements, which can be examined further in Figure 4.

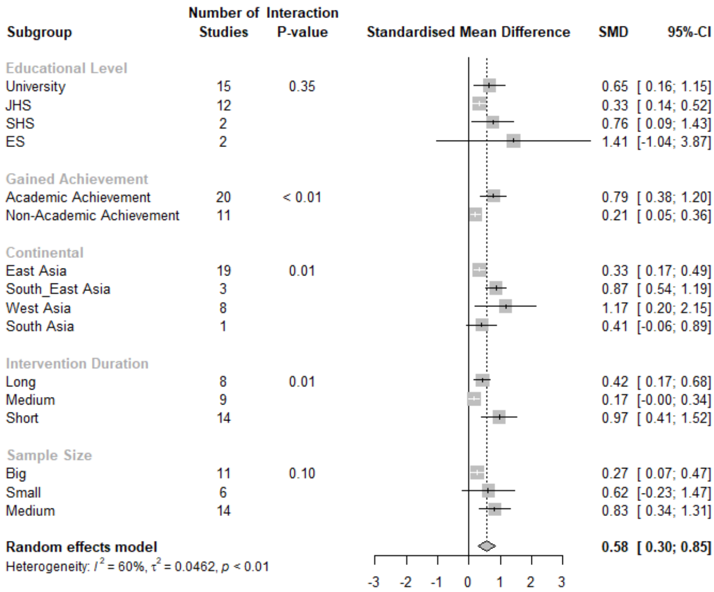

Figure 4. Forest plot variable moderator

Figure 4. Moderator variable analysis in this meta-analysis shows the moderating effect of several factors on the relationship between the use of AI-based learning media and student achievement. The analysis results show that the factors of education level and sample size do not significantly influence this relationship. Meanwhile, the achievement factors achieved, and the continent and length of intervention significantly influence the relationship between the use of AI-based learning media and student achievement. These two conclusions can be observed from the p-value of each factor. Two factors that did not have a significant influence had a p-value > .05; conversely, the factors that were proven to have a significant influence had a p-value < .05.

From the meta-analysis results on moderator variables presented in Figure 4, the impact of AI-based learning materials on student accomplishment is influenced by several moderator variables. According to the findings, educational level (university, JHS, SHS, and ES) is not a significant mediator of educational level (p-value = 0.35). Nonetheless, some research indicates that AI works better at lower educational levels since younger, tech-savvy pupils are more receptive to AI-based teaching strategies (Hwang, 2022). The application of AI has a statistically significant ($p < 0.01$) impact on academic accomplishment (SMD = 0.79) as opposed to non-academic achievement (SMD = 0.21), according to Gained accomplishment (Type of Achievement Achieved). These results are supported by research by (Zheng et al., 2023), which indicates that AI will probably enhance students' academic comprehension, particularly in areas like physics and mathematics that call for analytical abilities.

The impact of AI on achievement differs by region for Continental (Region), with West Asia seeing a more significant effect (SMD = 1.17) than East Asia (SMD = 0.33). This might have to do with how regional variations in technology infrastructure and investment impact the use of AI in classrooms. According to a study by Hwang (2022), infrastructure preparedness and technological accessibility are critical factors in the success of AI in education. Next, it was discovered that the length of the intervention was a significant moderator (p-value = 0.01), with a longer period showing a more pronounced effect (SMD = 0.97). These results are corroborated by Zheng et al. (2023), who show that longer length enables AI to adjust to the needs of individual students more effectively, boosting its efficacy in raising success.

Lastly, studies with smaller samples typically exhibit a more significant effect (SMD = 0.62), although sample size does not demonstrate a significant influence (p-value = 0.10). Better control factors in small-sample research may cause this, enabling more intensive and targeted AI applications. According to the information gathered for this meta-analysis study, AI in education positively impacts academic attainment. This is especially true if interventions are tailored to the local educational context and last sufficient time.

The findings of a meta-analysis on this mediator variable provide more evidence that using learning materials based on artificial intelligence (AI) in the classroom has had a significant effect on students' academic performance. However, the outcome may differ based on the circumstances and features of the intervention. The findings of this study are corroborated by a meta-analysis by Hwang (2022), which demonstrates that AI positively impacts the mathematical proficiency of primary school pupils, with an effectiveness value of approximately 0.351. However, some moderating factors, such as the subject of mathematics instruction and the student's educational attainment, might impact this outcome.

However, a different study by Zheng et al. (2023), which examined 24 articles, also demonstrated that AI significantly impacted learning accomplishment, particularly concerning students' comprehension of the material. The effectiveness of AI is influenced by several factors, including sample size, education level, learning domain, and the function of AI in learning. According to this study, adaptive learning and intelligent tutorial systems—two examples of personalized AI technologies—improved students' academic performance more than traditional teaching techniques. Therefore, this meta-analysis supports the finding that incorporating AI into educational learning materials can significantly increase student accomplishment, particularly when customized to each student's needs and traits.

Conclusion

Integrating technology in the form of artificial intelligence, especially in the form of learning media needs to be developed and become the focus of all educational parties. This is because AI-based learning media has been proven to impact students' academic and non-academic achievements significantly. This meta-analysis result implies that the modifications to AI interventions depend on the educational level; teachers should consider incorporating AI specific to each student's requirements and cognitive growth. For example, they should emphasize interactive elements for elementary school pupils and analytics-based apps for college students. Furthermore, student achievement was more significantly impacted by an intervention that lasted longer. This demonstrates how crucial it is to plan using AI-based learning materials over an extended period to improve teaching strategies' adaptation and personalization. To promote students' ongoing academic progress, educators and curriculum designers should create long-term structured AI-based learning programs.

This argument, which is the significance of investing in technology in particular fields, is a reasonably required implication. The success of implementing AI depends critically on the preparedness of the technological infrastructure, as demonstrated by the effectiveness of AI in various locations (e.g., East Asia versus West Asia). To guarantee that AI can be applied successfully and fairly, governments and educational institutions in areas with inadequate infrastructure must boost investments in technology and training. Overall, this study's results indicate that using AI-based learning media can potentially improve student accomplishment.

Conflict of Interest:

The authors state that they have no competing interests regarding this article's publication and no personal or financial ties to any groups or people that might improperly affect the direction or results of the research.

Research Involving Human Participants and/or Animals:

No humans or animals were involved in this scientific project. This study's research does not involve direct interaction with humans or animals **but** is based on secondary data from previously published sources.

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Appendix **1.** The Collected Study

Study	evel	Achievement	Model AI	Country	Duration (Weeks)
Study1	Univ	Design and implement system software	AI-enabled personalized video recommendation	Taiwan	12
Study2	Univ	Learning Outcome/High	AI-enabled personalized video recommendation	Taiwan	12
Study3	Univ	Learning Outcome/Medium	AI-enabled personalized video recommendation	Taiwan	12
Study4	Univ	Learning Outcome/Low	AI-enabled personalized video recommendation	Taiwan	12
Study5	JHS	Triggered-Interest in Reading	Chatbot, Sister Fish	Taiwan	6
Study6	JHS	maintained-Feeling in Reading	Chatbot, Sister Fish	Taiwan	6
Study7	JHS	maintained-value in Reading	Chatbot, Sister Fish	Taiwan	6
Study8	JHS	Reading Interest	Chatbot, Sister Fish	Taiwan	6
Study9	JHS	Attention in Reading	Chatbot, Sister Fish	Taiwan	6
Study10	JHS	Control in Reading	Chatbot, Sister Fish	Taiwan	6
Study11	JHS	Curiosity in Reading	Chatbot, Sister Fish	Taiwan	6
Study12	JHS	Interest in Reading	Chatbot, Sister Fish	Taiwan	6
Study13	JHS	Flow in Reading	Chatbot, Sister Fish	Taiwan	6
Study14	SHS	Learners' performance	AI-driven personalized learning	Taiwan	2
Study15	JHS	Speaking Performance	Lyra Virtual assistance	Indonesia	4
Study16	Univ	Students' performance	Flipped Classroom AI-assisted	China	16
Study17	ES	Learning Outcome	Chatbot	Turki	4
Study18	JHS	Digital Literacy	AI-based Video	Indonesia	3
Study19	JHS	Learning Outcome	AI-based Video	Indonesia	3
Study20	ES	Scientific understanding	AI-based material	China	4
Study21	Univ	Learning Achievement	AI mediated instruction	China	10
Study22	Univ	Motivation	AI mediated instruction	China	10
Study23	Univ	Self-Regulation	AI mediated instruction	China	10
Study24	Univ	Achievement	AI-supported animated infographic	Saudi Arabia	4
Study25	Univ	Visual Thinking	AI-supported animated	Saudi Arabia	4

			infographic		
Study26	Univ	Willingness to learn	AI-supported animated infographic	Saudi Arabia	4
Study27	Univ	Achievement Test	AI-enabled e-learning	Saudi Arabia	4
Study28	Univ	Learning Process	AI-enabled e-learning	Saudi Arabia	4
Study29	Univ	Cognitive Achievement	AI-enabled e-learning	Saudi Arabia	4
Study30	Univ	Students' achievement	AI strategy-based educational software	Jordan	3
Study31	SHS	Learning Achievement	AI-assisted learning	India	3