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Enhancing Student Learning Outcomes Through Experiential Learning Practices: A Meta-Analysis

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Abstract

Implementing the experiential learning model is one effective step in improving student learning outcomes, but recent evidence regarding its effectiveness is still inconsistent and not widely reported. Therefore, to gain a deep understanding and identify the effectiveness of experiential learning practices, this meta-analysis review was conducted. This review was conducted on 23 studies with 40 effect sizes obtained from the Scopus, ERIC, and Web of Science databases. The analysis model used was a random effects model with a robust variance estimation (RVE) approach to address the issue of interdependence between effect sizes within a single study. The measurement results show a high overall effect size (Hedges's g = 1.15; 95% CI), indicating a significant positive impact. Heterogeneity estimates are very high (I^2 = 98.2%), requiring further moderator analysis. Meta-regression analysis of the variables of education level, treatment type, and learning outcome dimension showed that only the education level variable approached significance in moderating the variation in learning outcomes. Subgroup analysis showed variation in the effectiveness of intervention implementation within each moderator category, but all were within the positive range. Publication bias tests showed bias, but correction using the trim-and-fill method and Peter's test proved that these findings remained consistent and valid. Overall, experiential learning has proven effective in enhancing and shaping various dimensions of student learning outcomes. This approach has great potential to continue being used and integrated into future learning practices, especially through the support of various pedagogical innovations and technology integration.

Keywords: Experiential Learning; Learning Media; Learning Outcomes; Meta-Analysis

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INTRODUCTION

The rapid development of technology and the strong flow of information currently occurring pose various new challenges to life (Hebebci & Crompton, 2023). From digital distractions and the digital literacy gap, to growing environmental problems and sustainability issues. This condition demands the mastery of various basic competencies, such as optimal cognitive abilities, problem-solving skills, critical thinking skills, creativity (Haryaka et al., 2025; Phinla et al., 2025), sustainability awareness (Hajj et al., 2024), and technological literacy (Zou et al., 2025), in order to remain adaptable and relevant. This situation presents a demand for educational institutions to equip and train these various basic competencies Through the practices and learning processes they implement. According to Dewey, a good learning process is one that can accommodate students' daily lives and experiences, and make students the main actors in their own learning (Hughes et al., 2025; Ling et al, 2023). Learning activities based on contextual experiences and hands-on practice are believed to produce deep and meaningful knowledge (Rivera, 2024), as well as optimally promote the development of various other learning competencies (Kerrigan & Kwaik, 2024). One learning model that meets these characteristics is experiential learning (Jonathan & Laik, 2019).

The Experiential Learning model was introduced by David Kolb in 1984, as a synthesis of various ideas and concepts from educational theorists and practitioners (Meyer & Seaman, 2021). This model emphasizes that knowledge is formed through the process of processing and transforming the experiences students possess and undergo (Kolb, 2015). According to Kolb, learning is a continuous cycle that begins with real-world experience, followed by a reflection process to generate concepts, which are then tested through active experimentation (Navarro et al., 2024). Through this cycle, students not only gain conceptual understanding but also develop practical skills and form various positive attitudes (Dorland, 2024).

Experiential learning has been widely implemented in educational practices at various levels, from preschool and elementary school to higher education (Morris, 2020). Fields such as medicine and engineering have long applied this model in their learning activities (Thomas et al., 2025; Steele, 2023). Previous research applying experiential learning has reported varied results, both in terms of effectiveness and the types of competencies or learning outcomes that can be developed. Research by Indriani and Mercuriani (2020), found that students in the experimental group who learned using the experiential learning model achieved lower learning outcomes compared to the control group. However, in other studies such as Kim dan Kim (2021) and Chen et al (2025), it was found that experiential learning actually improved student learning outcomes more optimally compared to traditional learning. This highlights the importance of synthesizing previous research to gain a more comprehensive understanding of the impact of experiential learning models.

Various previous studies using meta-analysis methods to measure the effectiveness of experiential learning in improving student learning outcomes are still limited, with some focusing only on a specific form of competence or learning outcome (Huda et al., 2025) or being conducted only on specific groups or educational levels (Zhang et al., 2021). A meta-analysis study conducted by Burch et al (2016) on 53 studies found a combined effect size of 1.036, which is categorized as very high. This finding indicates that experiential learning has high effectiveness in improving student learning outcomes compared to traditional groups or classes. However, this study has not reported and further analyzed various factors or variables that may influence the results or effectiveness of the intervention performed, has not conducted publication bias testing, and was carried out with inadequate analytical methods, therefore the conclusions presented are not sufficiently convincing. Another study by Burch et al (2019), which analyzed 89 studies published up to 2017, found similar conclusions with a combined effect size value of 0.43, which falls into the moderate category. This study also identified several moderating variables, such as the form or dimension of learning outcomes, type of assessment, feedback, and duration of study. Unfortunately, this study has also not yet fully conducted a series of tests or advanced analyzes, such as heterogeneity analysis, subgroup analysis, and publication bias testing. Additionally, the two-level meta-analysis method or approach used has significant potential for bias, as the number of studies and effect sizes analyzed is quite large, raising doubts about the validity of the reported results.

The above issues indicate that there is still a need for more recent meta-analysis studies that can complement and expand on previous findings, providing a more optimal and up-to-date overview. The meta-analysis conducted in this study will focus on various studies published in the last five years, including recent studies that combine experiential learning with innovative learning approaches such as STEM, as well as the use of diverse learning device and media innovations, including VR or AR-based media, AI-powered chatbots, digital games, and robotic media. To improve the accuracy of the analysis, this study uses a robust variance estimation approach within a random-effects model to address the issue of effect size dependence. In addition, a series of tests and analyzes will be conducted on moderator variables, potential publication bias, and sensitivity analysis to ensure the overall validity and consistency of the analysis results.

The entire process of this research will be conducted to answer several research questions, including: 1) what is the overall effect size of the experiential learning model in influencing student learning outcomes; 2) what is the influence of moderator variables on student learning outcomes; 3) what are the potential biases and robustness of the reported analysis results; and 4) what are the future opportunities for experiential learning.

METHOD

This study uses a meta-analysis approach to synthesize various previous studies or literature related to the implementation of the experiential learning model and its influence on student learning outcomes. The research was conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Moher et al., 2015). Overall, the research stages include problem definition and research question formulation, identification of databases and literature search strategies, screening based on inclusion and exclusion criteria, data extraction and quality assessment, and finally, the coding and meta-analysis process.

Search Strategy & Eligibility

The process of literature search and collection was conducted through the Scopus, Web of Science, and ERIC databases. The selection of these three databases was based on considerations of ease of access and the quality assurance of the available literature, given that all articles have undergone a rigorous peer review process. The literature search was conducted at the beginning of September and concluded on September 16, 2025, covering publications from 2020 to the end of August 2025. The process of searching for and collecting literature was carried out using the keywords "Experiential Learning", "Experiential Learning Model", "Learning Outcomes", "Learning Achievement", "Learning Competencies", and "Learning Skills". The selection of these keywords was aimed at gathering more relevant literature to support the research needs. Boolean operators such as "AND" and "OR" are also used to improve the effectiveness of literature searches and collection.

The literature to be analyzed focuses on recent studies written and presented in English to make them easier to analyze. Literature searches were also conducted by including studies in the format of conference proceedings and journal articles to obtain more studies relevant to the research objectives and data needs. To avoid potential bias due to differences in quality between studies, a series of advanced risk of bias analyzes will be conducted. In addition to the criteria mentioned above, there are several advanced criteria also used to ensure the quality of the studies to be analyzed. These various criteria are included in the inclusion and exclusion criteria presented in Table 1.

Table 1. Inclusion and exclusion criteria

Component	Inclusion Criteria	Exclusion Criteria
Learning Model	Applying the experiential learning model as an intervention or treatment for students.	Not implementing or using the experiential learning model as a treatment or intervention for students.
Publication Date	Studies published between January 2020 and August 2025	Studies published before January 2020 or after August 2025
Type of publication	Studies in the form of journal articles or conference proceedings that have undergone peer review	Studies in the form of book chapters, reports, and opinions will be excluded.
Language	The study is written in English.	Studies not written in English will be excluded.
Research design	This is an empirical study with a quasi-experimental or true experimental design.	Studies that do not use a quasi-experimental or true experimental design will be excluded.
Research findings	The study must report student learning achievements or results after treatment for both the experimental and control groups, including data on the number of subjects in each group, mean scores, and standard deviation.	Studies that do not report some or all of the required data, such as the number of subjects in each group, mean values, and standard deviations, will be excluded.

Screening & PRISMA

The entire literature was selected and evaluated using the Covidence software, then reported in a PRISMA plot as shown in Figure 1. The selection and review process were conducted in three stages, including entering data into the Covidence software and removing duplicate or duplicated articles. Out of a total of 591 studies, 579 remained for further review. In the second stage, the review focused on the titles and abstracts of each study, resulting in 83 studies that met the criteria to proceed to the third review stage. At this stage, the entire study was read and analyzed more comprehensively, leaving 23 studies for further analysis. The selection and analysis stages are carried out by two assessors, and any differences or conflicts that arise are resolved by an independent assessor to reach a final conclusion regarding the studies to be included in the analysis and subsequent stages.

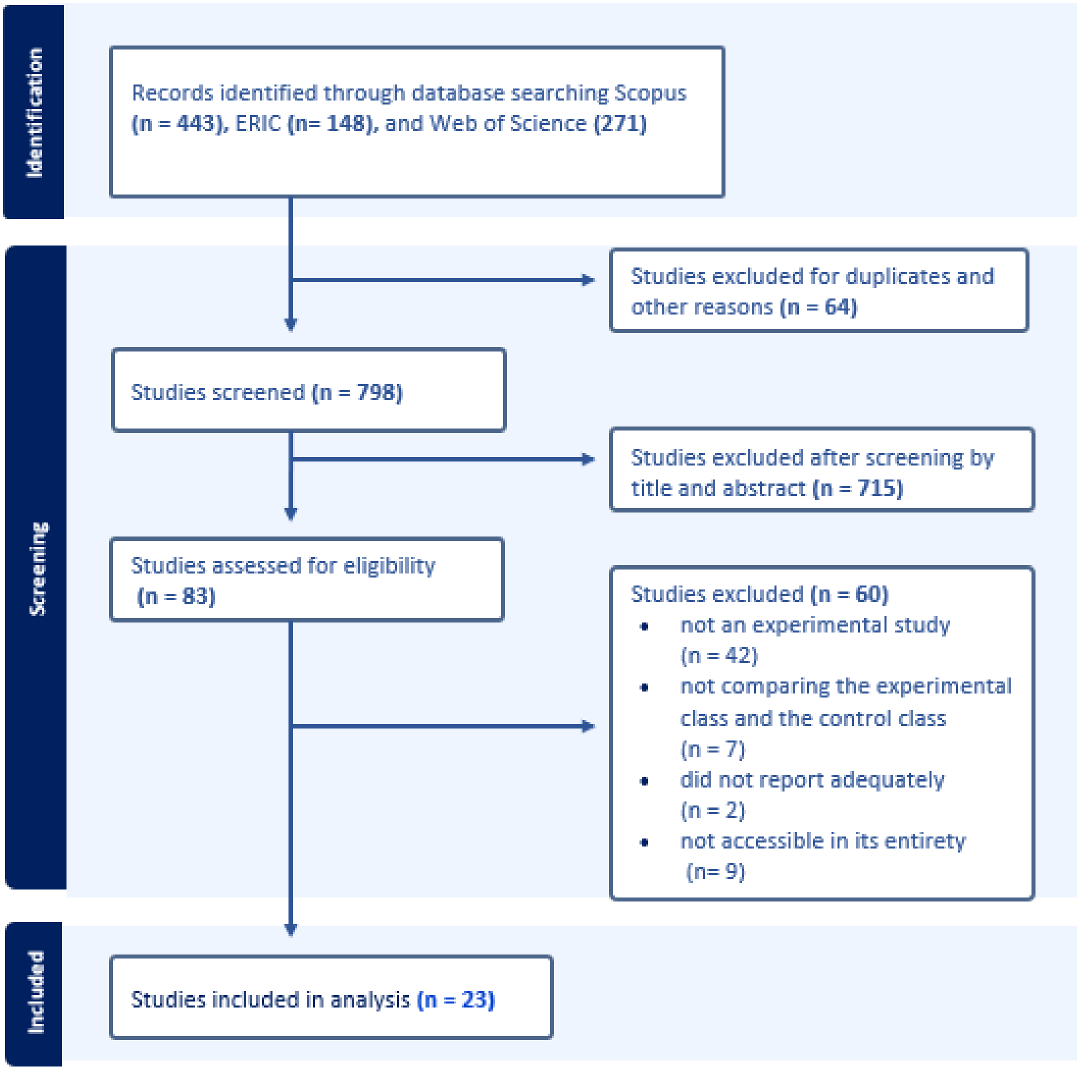

Figure 1. Flowchart of the literature selection process

Coding & Reliability

After going through a screening stage based on predetermined criteria, as well as various other strict selection stages, the studies were coded following the guidelines proposed and validated by Siddiq et al (2016), The coding process was carried out by mapping study identities such as author names, year of publication, and other key information including sample size in each class, mean, and standard deviation. Additional information was also recorded regarding the moderator variables, namely education level, treatment, and the form or dimension of learning outcomes measured. A complete guide to the techniques and methods of coding used is shown in the codebook's Table S1 in the appendix section. The entire analysis and coding process was carried out by two people, and to ensure consistency and objectivity in the literature selection process, a reliability test was conducted using Cohen's Kappa (κ). The calculation results show a κ value of 0.94, which indicates a very high level of agreement (almost perfect agreement) between the two raters.

Effect Size Computation

After the analysis and coding process is completed, the next step is to calculate the effect size for each study using Hedges' g metric, which is a development of Cohen's d with correction for small sample bias (Moulaei et al., 2024). Effect size calculations were performed using posttest data from the control and experimental groups in each study. The complete calculation process included calculating the pooled standard deviation, then Cohen's d, small sample correction, and finally, calculations were performed using Hedges' g, which involved multiplying the Cohen's d metric calculation results by the J correction factor. To obtain the confidence interval, the variance of Hedges' g was calculated (Hedges & Olkin, 1985). The entire calculation process uses the following formula.

Formula for calculating the pooled standard deviation

$$S_{pooled} = \sqrt{\frac{(n_e - 1)\, Se^2 + (n_c - 1)\, Sc^2}{n_e + n_c}}$$

Formula for calculating Cohen's d

$$d = \frac{\bar{x}_e + \bar{x}_c}{S_{pooled}}$$

Formula for calculating the correction for small sample size

$$\mathrm{J} = 1 - \frac{3}{4(n_e + n_c) - 9}$$

Formula for calculating Hadges' g

$$\mathrm{g} = d\ x\ J$$

Next, Hedges' g variance is calculated using the following formula

$$Var_{(g)} = 1 - \frac{n_1 + n_2}{n_1\ n_2} + \frac{g^2}{2(n_1 + n_2)}$$

For studies reporting more than one measurement result due to the use of multiple treatments, different sample groups, or measurement of more than one learning outcome dimension, all reported results will be included in the analysis to calculate the effect size. Each effect size obtained from the same study will be considered a dependent sample, allowing all relevant and available data from each study to be utilized for a more in-depth analysis.

Effect Size Computation

The statistical model used in this analysis is the random effects model, which was chosen because it can accommodate studies with high potential heterogeneity due to differences in participant characteristics, intervention types, and research settings (Wang et al., 2020). The combined effect was estimated by calculating the weighted average of the effects from each study, where the weights were based on the total variance, which is the combination of within-study variance and between-study variance. Heterogeneity parameters (Q, I^2, and τ^2) were estimated using the REML (Restricted Maximum Likelihood) method (Trong et al., 2022).

To address the condition where a single study reports more than one effect size, leading to interdependence between the analyzed effects and potentially violating the assumption of data independence, the Robust Variance Estimation (RVE) method is used. RVE allows for more accurate estimation of variance and confidence intervals by accounting for the correlation between effects originating from the same study, ensuring that the analysis results remain valid and reliable despite the presence of correlated multiple effects (Pustejovsky & Tipton, 2022).

Next, to delve into the factors that might moderate the variation in effects across studies, meta-regression and subgroup analyzes were conducted. Meta-regression calculates the simultaneous influence of moderator variables on effect size, helping to identify sources of heterogeneity (Borenstein et al., 2021) and the impact of factors such as education level, type of intervention, and learning outcome dimensions. Subgroup analysis was conducted to compare the effects between groups separately based on specific moderator categories, providing a more detailed picture of the variation in effects within the study subpopulation (Cheng et al., 2021).

Risk of Bias

To measure the risk of bias in the analysis performed, the Effective Public Health Practice Project (EPHPP) assessment tool was used. EPHPP is considered valid and reliable for assessing the methodological quality of quantitative studies, such as in the context of studies or research in the field of education (Nowell et al., 2022). This tool evaluates several key domains including participant selection, study design, confounding factors, blinding, data collection methods, and withdrawal/dropout (Knoke et al., 2024). Each domain is given a score that describes the risk of bias, which is strong, moderate, or weak.

In addition to assessing the risk of bias in each selected study, an evaluation of the potential for publication bias was also conducted through various testing steps, including visual testing using funnel plots to detect asymmetry as one indicator of potential publication bias by assessing the level of symmetry in the distribution of study effect sizes against their precision (Peters et al., 2008). Furthermore, several statistical tests were also performed to strengthen confidence and correct for potential publication bias, such as Egger's test to quantitatively detect asymmetry in the funnel diagram by examining the relationship between effect size and standard error, where a significant result indicates the potential for publication bias (Egger et al., 1997), followed by the trim and fill method to estimate and adjust for potential publication bias. This method works by identifying and "filling in" missing studies on a funnel plot, resulting in an estimate of the combined effect size corrected for potential publication bias (Nakagawa et al., 2022), as well as Peter's test to assess whether the distribution of effect sizes from the analyzed studies is distorted due to publication bias (Seighali et al., 2024)

Data Analysis

The overall analysis steps to be taken include calculating the effect size for each study using the standardized mean difference (Hedges' g). Subsequently, the overall effect size was calculated using a random-effects model through the application of the Robust Variance Estimation (RVE) method to accommodate inter-study heterogeneity and address the issue of dependent samples. The combined effect is calculated as a weighted average, with weights based on the total variance. Heterogeneity tests were conducted using the Q, I^2, and τ^2 parameters, which were estimated using the REML (Restricted Maximum Likelihood) method.

Next, a sensitivity analysis was conducted to ensure the stability, validity, and reliability of the analysis results. Various approaches were applied, including influence diagnostics using the leave-one-out method and Baujat plots to detect studies that significantly contributed to the pooled effect and heterogeneity. Additionally, outlier-resistant estimation is applied to reduce the impact of extreme values in the data, making the results more robust. The analysis stage was also expanded by comparing estimator variations, trimming outlier studies, and testing the differences in results between models with and without dependence control (RVE versus non-RVE).

Meta-regression analysis was conducted to explore the influence of moderator variables on the effect, followed by subgroup analysis to identify differences in the effect based on the moderator categories. Additionally, publication bias risk analysis was conducted using visual inspection of funnel plots, Egger's test, trim-and-fill procedures, and Peter's test to detect and correct for potential publication bias.

RESULTS

Study Characteristics

This meta-analysis was conducted on 23 studies with a total of 40 effect sizes. Some studies reported more than one effect size because they measured more than one competency or learning outcome dimension, as well as in several different sample groups. The total number of participants in the control group was 1,372, and 1,374 participants or samples were included in the experimental group. Most studies were conducted at the higher education level (47.5%), followed by the senior high school level (22.5%), junior high school (20%), and elementary school (10%). In the implementation and practice of experiential learning, several studies reported the use of approaches (7.5%), methods (15%), and innovative learning media (62.5%). However, approximately 15% of the collected studies did not report additional treatments or special interventions used in the experiential learning practices. Experiential learning practices in the selected studies are aimed at shaping various dimensions of student learning outcomes, including knowledge (52.5%), skills (20%), and attitudes (27.5%). A complete overview of the characteristics of the various studies analyzed is presented in Table A1.

The analyzed studies employed a quasi-experimental design, with sample sizes ranging from 17 to 130 students per group. All studies also conducted measurements or tests to assess the effectiveness of the treatment provided continuously after the treatment was completed, meaning there was no significant time gap between the treatment and the measurement or testing. Overall, the studies analyzed were dominated by research conducted in the Asian region, with Indonesia being the country with the most affiliations. However, some other studies were also conducted in the European and North American regions.

To ensure the quality of the analysis results, risk assessment becomes a crucial step that must be carried out. Selected studies were assessed for their feasibility and potential for bias using the Effective Public Health Practice Project (EPHPP) instrument. This instrument includes several main domains: selection bias, study design, confounders, blinding, data collection, withdrawals/dropouts, analysis, and intervention integrity (Knoke et al., 2024). The risk of publication bias was also carefully assessed for each study analyzed. The complete results of this biased risk assessment are presented in Figure 2.

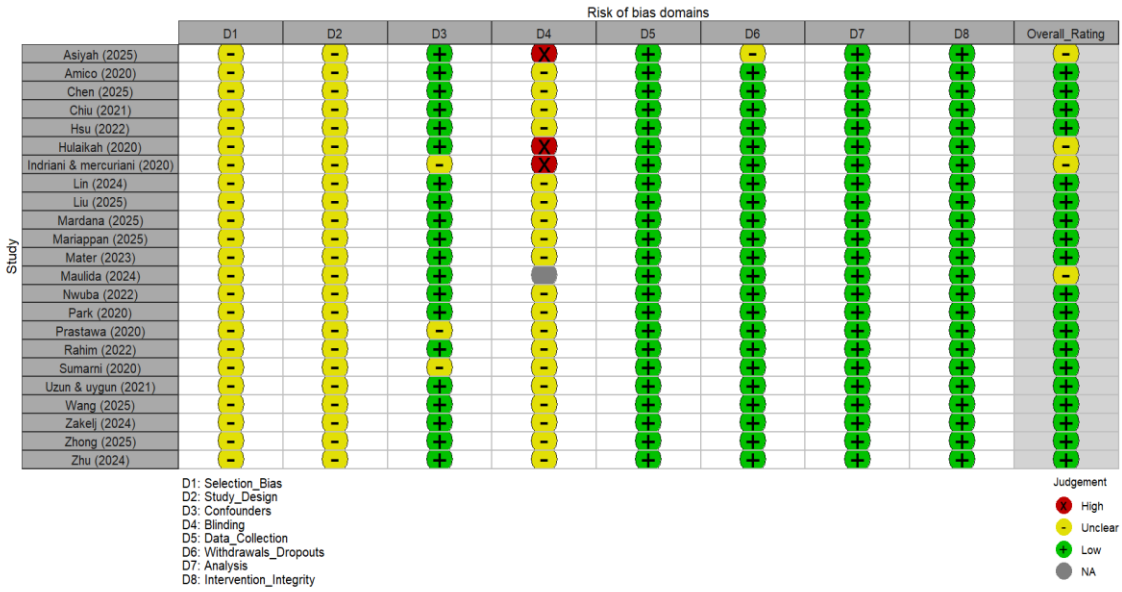

Figure 2. Table of bias risk assessment for each study

The majority of studies show a low risk of bias, indicated by the dominance of green color labels in each domain, particularly in the analysis, data collection, and withdrawals/dropouts domains. However, in some domains, there appears to be unclear potential for bias, marked by yellow color labels, especially in the selection bias and study design domains. This condition occurs because all studies used a quasi-experimental approach, where sample selection was not done randomly. Although the implementation process is carried out in a measured and strict manner, the potential for bias cannot be completely eliminated. Some studies also show a high risk of bias in the blinding domain, as neither the outcome assessor nor the participants were fully blinded to the intervention status. Additionally, there are studies that do not clearly report the blinding procedures or mechanisms used. Overall, the percentage of bias risk in each domain is shown in Figure 3.

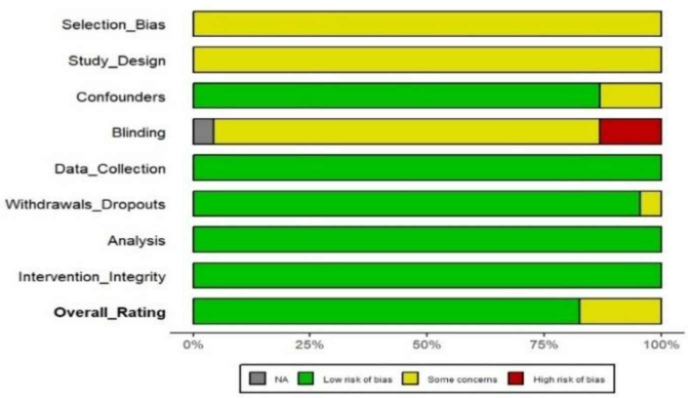

Figure 3. Summary diagram of bias risk assessment results for each domain

The summary of the bias risk assessment results in Figure 3 shows that the majority of the analyzed studies had a low risk of bias, with a percentage of approximately 80%. Some domains such as data collection, analysis, and intervention integrity even reported a low risk of bias with a percentage reaching 100%. High risk of bias was only found in the blinding domain with a percentage of approximately 15–20%, while the bias risk categories requiring special attention were shown in the selection bias and study design domains. Overall, it can be concluded that the studies analyzed are of good quality and have a low risk of bias, thus providing confidence in the validity of the analysis results to be reported.

This finding aligns with various previous studies that also conducted meta-analyses in the field of education, such as Chen et al (2023) and Yu & Xu (2022), which also reported that the majority of the analyzed studies used a quasi-experimental design with non-random sample selection. This condition is common in educational research because research in this field generally aims to capture the real-world situations and conditions of learning practices in schools and to implement interventions in as natural a setting as possible without overly strict intervention (Gopalan et al., 2020). Nevertheless, the use of systematic research protocols, strict oversight procedures, and structured analysis steps was maintained to ensure that the conclusions and results obtained remained valid and reliable.

The influence of experiential learning on student learning outcomes

The measurement of the overall effect size begins by calculating the effect size in each study using Hedges' g. Subsequently, the random effects method with Robust Variance Estimation (RVE) approach is used to obtain the pooled effect size, minimizing the issue of effect size dependence originating from the same study. Heterogeneity estimation was also performed to see the extent to which the results or effect sizes in each study differed, not solely due to chance. Heterogeneity testing was performed using the Q statistic, the I^2 parameter, and τ^2 (tau-squared), which were estimated using the Restricted Maximum Likelihood (REML) method. The following presents the results of the overall effect size measurements and heterogeneity tests from various studies collected in Table 2.

Table 2. Overall Effect Size and Heterogeneity

Overall Effect Size						Heterogeneity				
k	m	Hadges'g	SE	95% CI		τ^2	I^2	Q	df	prediction interval
				Lower	Upper					
23	40	1.15	0.24	0.67	1.64	3.80	98.2%	541.81	39	-2.56, 5.18

Table 2 shows a summary of the measurement results that have been conducted, where the combined effect size obtained is 1.15 with a standard error of 0.24 and a 95% confidence interval (0.67–1.64). This combined effect size falls into the high category (large effect) (Cohen et al., 2018), indicating that the application of the experiential learning model is proven effective in improving student learning outcomes compared to students who did not receive similar treatment or learning. Heterogeneity estimates show a Q value of 541.81, τ^2 (tau-squared) = 3.80 (SE = 0.89), and I^2 = 98.2%. These values indicate high heterogeneity between studies, suggesting that the observed differences in results are not solely due to statistical chance, but also to real differences in the research context, participant characteristics, and the form of intervention applied in each analyzed study. Additionally, the prediction interval obtained, which ranges from -2.56 to 5.18, indicates a possible and reasonable range of effects to be expected in future studies with similar contexts or topics. A wide prediction interval indicates the potential for future studies to yield both non-significant and significant results (IntHout et al., 2016), regarding the application or implementation of experiential learning.

To increase confidence and ensure the robustness of the measurement results, further analysis was conducted by comparing the pooled effect sizes obtained from several different models and estimators, such as DerSimonian Laird (DL) and REML, two-level models with RVE, and analyzes with and without outliers. The series of results from the comparison of combined effect sizes for each of these tests are reported in Table 3.

Table 3. Comparison of the overall effects of various testing scenarios

Scenario	Hadges's g	SE	95% CI	
			Lower	Upper
REML, 2-level, All	1.31	0.31	0.70	1.92
DL, 2-level, All	1.15	0.16	0.84	1.46
RVE, All	1.15	0.24	0.67	1.64
REML, 2-level, No Outlier	1.07	0.22	0.63	1.51
RVE, No Outlier	1.01	0.20	0.61	1.42

Table 3 shows that the combined effect size estimate is relatively consistent across analysis approaches. In the two-level random effects model with the REML estimator for the entire dataset, the largest pooled effect was obtained ($g = 1.31$; SE = 0.31; 95% CI: 0.70–1.92). Estimation with the DerSimonian–Laird (DL) estimator yielded slightly lower effect size values ($g = 1.15$; SE = 0.16; 95% CI: 0.84–1.46). The Robust Variance Estimation (RVE) approach also produced similar effect size values ($g = 1.15$; SE = 0.24; 95% CI: 0.67–1.64), and a decreasing trend in effect size was observed when the analysis was performed without outlier databoth in the two-level REML ($g = 1.07$; SE = 0.22; 95% CI: 0.63–1.51) and in the RVE ($g = 1.01$; SE = 0.20; 95% CI: 0.61–1.42).

Overall, both the inter-method variation and the presence of outliers did not significantly alter the main findings, as all effect size values remained in the high category and the confidence intervals showed statistical significance. This indicates that the results obtained are valid and reinforces that the application of experiential learning has high effectiveness in improving student learning outcomes.

The high effectiveness of experiential learning in improving student learning outcomes is possible because this approach provides students with the opportunity to actively engage in the learning process (Le et al., 2023; Sharma et al., 2025) and makes students' diverse experiences a central part of the learning process (Blankesteijn, 2024). This finding aligns with previous research results, which also reported that experiential learning helps students optimize their learning process, thus positively impacting maximum learning achievement (Kong, 2021; Syafriani et al., 2025).

High heterogeneity indicates that in the implementation of learning, there are various factors influencing its effectiveness and quality (Molendijk et al., 2025). In the context of experiential learning, student conditions and characteristics play an important role. Students from certain social and cultural backgrounds often exhibit different learning tendencies compared to other groups, necessitating adjustments to the learning process provided (Barak & Yuan, 2021). In addition, the role of the teacher and the quality of learning are also key factors for success (Amtu et al., 2020), because at every stage of learning, the teacher's role is still needed, whether as a validator, director, or facilitator of the learning process (Engida et al., 2024). Various other factors such as the utilization of media and learning devices, the availability of facilities and infrastructure, and the learning environment also contribute to the effectiveness of students' learning processes and the achievement of learning objectives (Bonem et al., 2020; Yangambi, 2023).

In addition to looking at the overall effect size, it is also important to review the effect size in each individual study to gain a deeper understanding of the effectiveness of experiential learning in improving student learning outcomes. A summary of the effect size for each study is visualized through a forest plot in Figure 4.

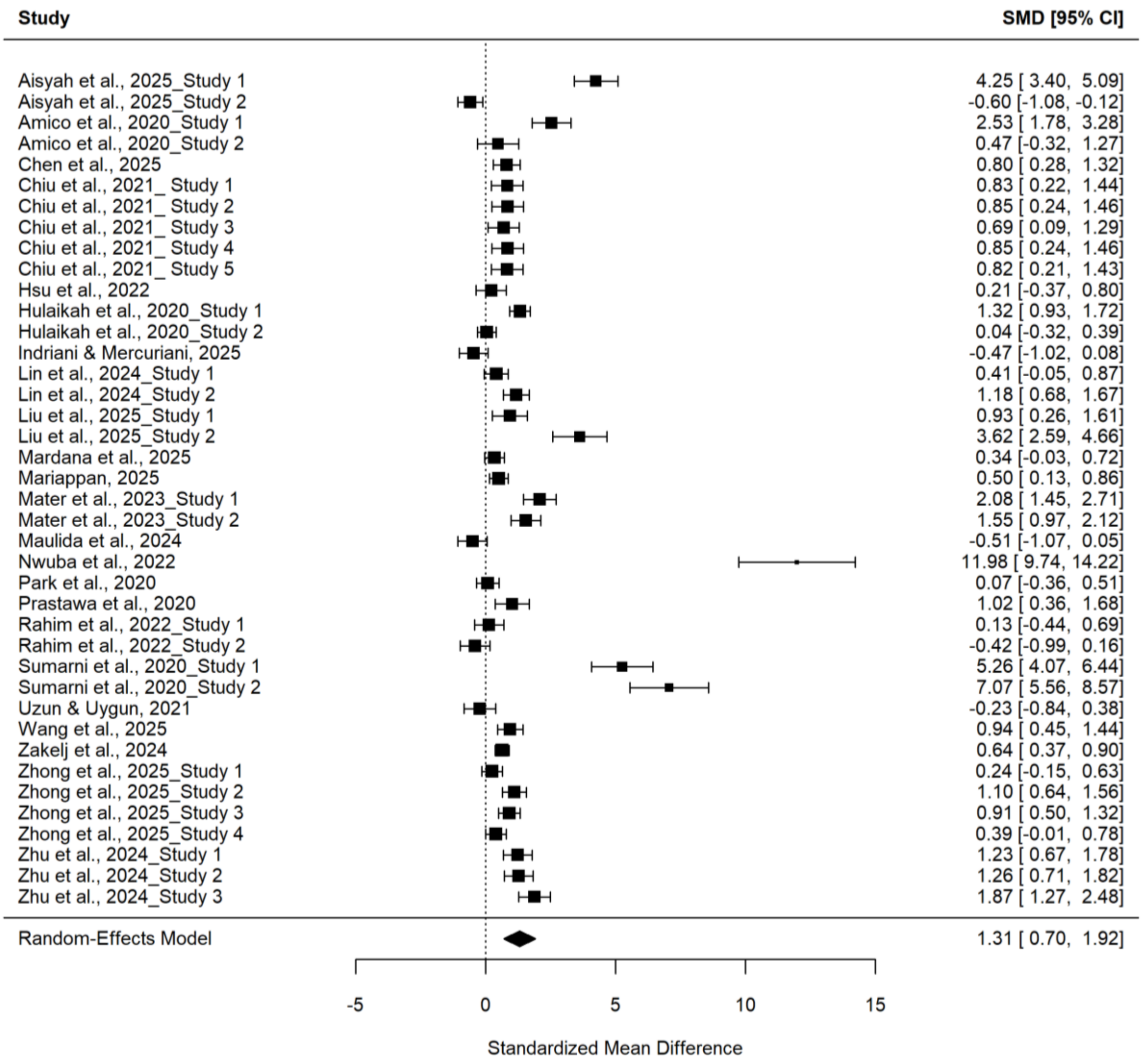

Figure 4. Forest Plot

Based on the forest plot (Figure 4), it is evident that there is a fairly clear variation in the effect sizes across the studies analyzed. Several studies, such as those conducted by Sumarni et al., Amico et al., Mater et al., Zakelj et al., Lin et al., and Zhu et al., show a high effect size, indicating that experiential learning interventions make a significant difference in student learning outcomes compared to the control group. However, one study was found to show a very high effect size and potential to be an outlier, namely the study by Nwuba et al.

Meanwhile, several studies, such as those conducted by Park et al., Zhing et al., and Chiu et al., showed a moderate effect size, indicating that the interventions applied were quite effective and had a significant impact on the development of the measured competencies. Conversely, there are also studies with small effect sizes, such as those by Wang et al., Rahim et al., Zhu et al., and Lin et al.; in fact, the study by Maulida et al. showed a negative effect size. A small or negative effect size value indicates that the learning outcomes of students in the control group were not significantly different, or even higher, compared to the experimental group. Thus, the effectiveness of experiential learning interventions in those studies can be categorized as low.

Some studies showing very high effect sizes compared to others are potentially outliers, so detection and sensitivity testing are needed to ensure the stability of the meta-analysis results. For this purpose, a diagnostic analysis was performed using a Baujat plot, which allows for the visual identification of studies with a significant contribution to heterogeneity and the pooled effect. The results of the box plot visualization are presented in Figure 5.

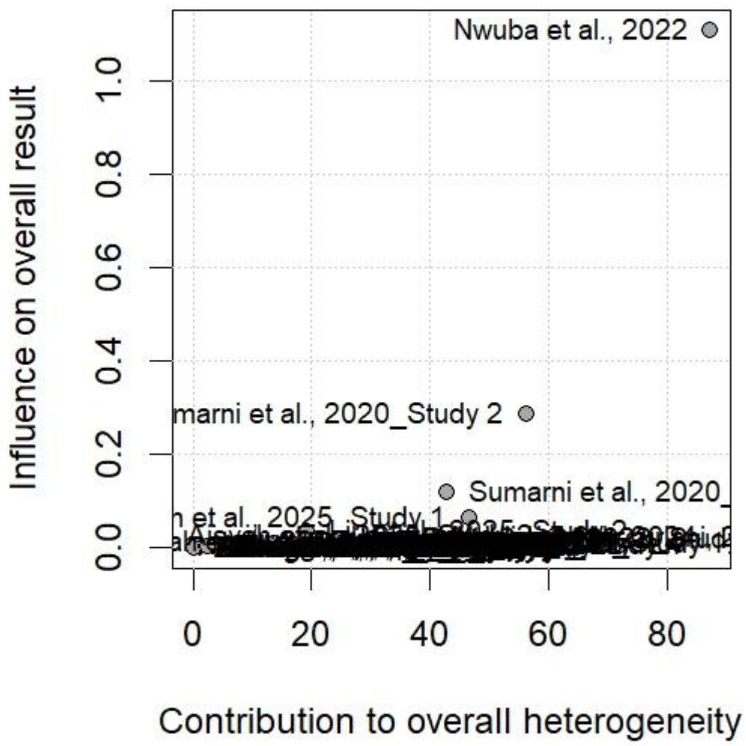

Figure 5. Bajut Plot

The bajut plot in Figure 5 shows that most studies have relatively small contributions and effects, as indicated by the pattern where several studies are clustered overall in the lower left area of the graph. However, there are several studies that appear more prominent, such as Nwuba et al. (2022), which has a significant impact on the overall results and shows clear potential outliers, as well as two dependent samples, namely Sumarni et al. (2020)_Study 2 and Sumarni et al. (2020)_Study 1, which also contribute significantly to the heterogeneity or overall impact of the results. To gain a clearer understanding of the influence of the studies identified as outliers, as well as some other studies that also showed high effect sizes, a sensitivity analysis was conducted using a leave-one-out approach. This analysis was performed by removing one study at a time and then recalculating the pooled effect size estimate each time a study was excluded from the analysis.

The results of the leave-one-out analysis show that the most significant change in the pooled effect size occurred when the Nwuba study was excluded, with the pooled effect size value dropping to 1.07 (95% CI: 0.63–1.51), and a slight decrease in heterogeneity parameters (τ^2 = 1.86 and I^2 = 96%). These findings support the suspicion that the Nwuba study is an outlier in this analysis. A summary and complete results of the leave-one-out testing can be found in Table C4.

The high variability in effect sizes across the analyzed studies indicates the need for further efforts to unravel and identify the factors influencing the magnitude of the effect sizes of the interventions applied. Therefore, meta-regression and subgroup analysis are important to conduct in order to test moderator variables. In this study, the moderator variables analyzed include education level, type of treatment, and the form or dimension of learning outcomes measured. Meta-regression and subgroup analysis are expected to provide a clearer picture of how these three moderator variables influence the effect size, quality, and outcomes of the experiential learning process implemented.

The influence of various moderator variables on the effectiveness of experiential learning

In addition to addressing and interpreting the high level of heterogeneity in the analyzed studies, meta-regression and subgroup analyzes are also intended to provide additional information regarding moderator variables, including specific actions or steps that can influence the quality and effectiveness of the interventions applied. The results of the meta-regression analysis showed that only the education level moderator variable exhibited a near-significant coefficient, specifically in the high school category ($b = 2.02$; $p = 0.084$). However, this significance only applies at a 10% confidence level, with the confidence interval still being very wide and including zero. Thus, in general, there are no significant moderator variables in explaining the variation in effect sizes across studies in this analysis. The complete results of the meta-regression analysis can be found in Table C3.

Next, subgroup analysis was conducted to provide a more detailed picture of the influence of each moderator variable on the intervention outcomes. Table 3 presents the results of the subgroup analysis based on three main moderator variables: education level, treatment type, and learning outcome dimension. A summary of the subgroup analysis results is presented in Table 4.

Subgroup analysis based on education level shows a fairly clear difference in the magnitude of the effect size at each level. Studies involving high school students yielded a very high effect size estimate of 3.42. These findings indicate that the implementation of experiential learning has a very strong impact on improving learning outcomes at that level. Meanwhile, the middle school student group achieved an effect size of 0.96, which is still considered high, followed by elementary school students (0.66) and university students (0.71), both of whom fall into the moderate category. This result indicates that the experiential learning model is most effectively applied at the high school level, although it still shows a good level of effectiveness at other educational levels. Interestingly, the results of the subgroup analysis at the elementary school level did not show any significant heterogeneity, as the values of the parameters τ^2 and I^2 were equal to zero. This condition is likely caused by the relatively small number of studies in that subgroup (only four studies) and the relatively uniform effect size, resulting in no substantial variation found between studies within that group.

Table 4. Results of subgroup analysis

Moderator Variables	Subgroup	k	Tau²	I² (%)	Hadges'g	Std. Error	P-Value
Dimensions of learning outcomes	Knowledge	21	1.02	94.36	0.82	0.23	0.0003
	Attitudes	11	3.5	97.56	1.29	0.57	0.0242
	Skills	8	14.33	99.41	2.76	1.35	0.0409
Level of education	Elementary school	4	0.0	0.0	0.66	0.09	<.0001
	Junior high school	8	1.63	94.85	0.96	0.47	0.0386
	Senior high school	9	15.93	99.03	3.42	1.34	0.0110
	College	19	0.24	79.71	0.71	0.13	<.0001
Treatment	Learning methods	6	9.72	99.31	2.07	1.29	0.108
	Learning media	25	0.96	92.73	0.98	0.21	<.0001
	Learning approaches	3	0.17	62.43	1.55	0.30	<.0001
	Not specified	6	21.21	99.72	2.14	1.89	0.258

This finding aligns with various previous studies that also concluded that learning practices emphasizing the active role of students and independent learning through a series of assignments and direct learning activities are more effectively delivered to older student groups (Siswanto, 2024). This is because students at this level are already capable of independently managing and planning their learning steps more optimally, and can explore more things without significant physical limitations (Hutasuhut et al., 2023). However, this doesn't mean that students in younger age groups, such as elementary school students, don't need to engage in learning that requires active participation and independent study. However, its implementation must be adapted to the students' cognitive development, social development, and physical condition (Martella et al., 2020; Li & Zeng, 2025).

Next, regarding the moderator variable of treatment received, the study group with the highest effect size was the learning method group with a combined effect size of 2.07, which falls into the very high category. This group of learning methods includes studies that apply experiential learning with various innovative methods, such as field studies, experiments, outdoor learning, simulations, and work practice. The high effect size indicates that the experiential learning model intervention, enhanced with various teaching methods, was able to increase the effectiveness of the intervention provided. Meanwhile, the study group that implemented the innovative learning approach also achieved a very high effect size of 1.55. This shows that innovative learning approaches like STEAM can optimize the implementation of experiential learning and improve student learning outcomes.

The third group consists of studies that combine experiential learning models with innovative learning media, such as robot media, AR-based learning media, AI-powered chatbots, and virtual game-based learning media. This group showed a large effect size, which was 0.98. This indicates that supporting the use of various innovative learning media can improve effectiveness and increase the opportunities for students to develop various learning outcome competencies. The final group consists of studies that do not directly describe the form of treatment administered. This group of studies also yielded an effect size in the very high category, which was 2.14. In its application, the experiential learning model generally involves several specific learning methods such as discussion and experimentation, which is why some studies do not specifically mention the form of the method used, as it has become part of the learning stages or syntax itself.

The results of the subgroup analysis indicate that all forms of treatment provided, whether in the form of approach, method, or the use of learning media, have a positive influence on students' learning outcomes (Tran-Duong, 2023; Thompson et al., 2023). This finding further confirms the importance of a learning process being carried out while considering the completeness of various essential or supporting elements and components. Learning approaches play an important role in guiding the course of the learning process (Hafeez, 2021), while teaching methods enable the learning process to be effective and followed by students (Razali & Nasri, 2023). In addition, the optimal learning process must also be supported by the availability of media or intermediaries that ensure information or lesson material can be delivered and understood well by students (Mahanani et al., 2025). Various previous studies have also reported that the presence of innovative learning approaches, such as STEM learning, can effectively improve student learning outcomes (Wan et al., 2023). Similarly, the use of technology-based methods and various media has proven effective in improving the quality of the learning process (Al-Barakat et al., 2025; Rizvi et al., 2025).

The final subgroup analysis was conducted by grouping studies based on the dimension or form of learning outcomes fostered, including: the knowledge dimension, which encompasses conceptual understanding, critical thinking, computational thinking, and knowledge retention; the skills dimension, which includes process skills, problem-solving, creativity, collaboration, and communication; and the attitudes dimension, which includes environmental awareness, disaster response attitudes, self-efficacy, and motivation.

The analysis results show that the intervention or treatment in the form of experiential learning has different effects on each group or dimension of learning outcomes. The skills dimension group had the highest effect size value, which was 2.76. This indicates that the intervention provided was highly effective in fostering and improving various student skills. The attitude dimension group also showed a very high effect size, which was 1.29. Meanwhile, the knowledge dimension group was in the high category with an effect size of 0.82. The results of this analysis indicate that experiential learning interventions have a significant impact on the formation and improvement of student learning outcomes, particularly in the dimensions of knowledge, skills, and attitudes.

Wang et al (2025) and Mater et al (2023) in their research also reported that experiential learning is proven effective for training and supporting the formation of various dimensions of student learning outcomes, both in the cognitive, affective, and psychomotor domains. Experiential learning models, through the stages of direct experience and deep reflection, are able to foster a deeper conceptual understanding in students (Bui & Yarsi, 2023), Additionally, the opportunity for students to directly design experiments or develop ideas in the form of projects during the active experimentation stage allows them to cultivate various practical skills (Javahery & Bavandi, 2025). Furthermore, active student participation in discussions and collaboration with peers or group members also helps shape important behaviors and attitudes such as sportsmanship, cooperation, and communication skills (Lingke, 2021; Hasan et al., 2023).

To gain a clearer understanding of the differences and the influence of each subgroup on the effect size obtained, Figure 6 presents a visualization in the form of a caterpillar plot, showing a summary of the effect sizes and their confidence intervals for each subgroup.

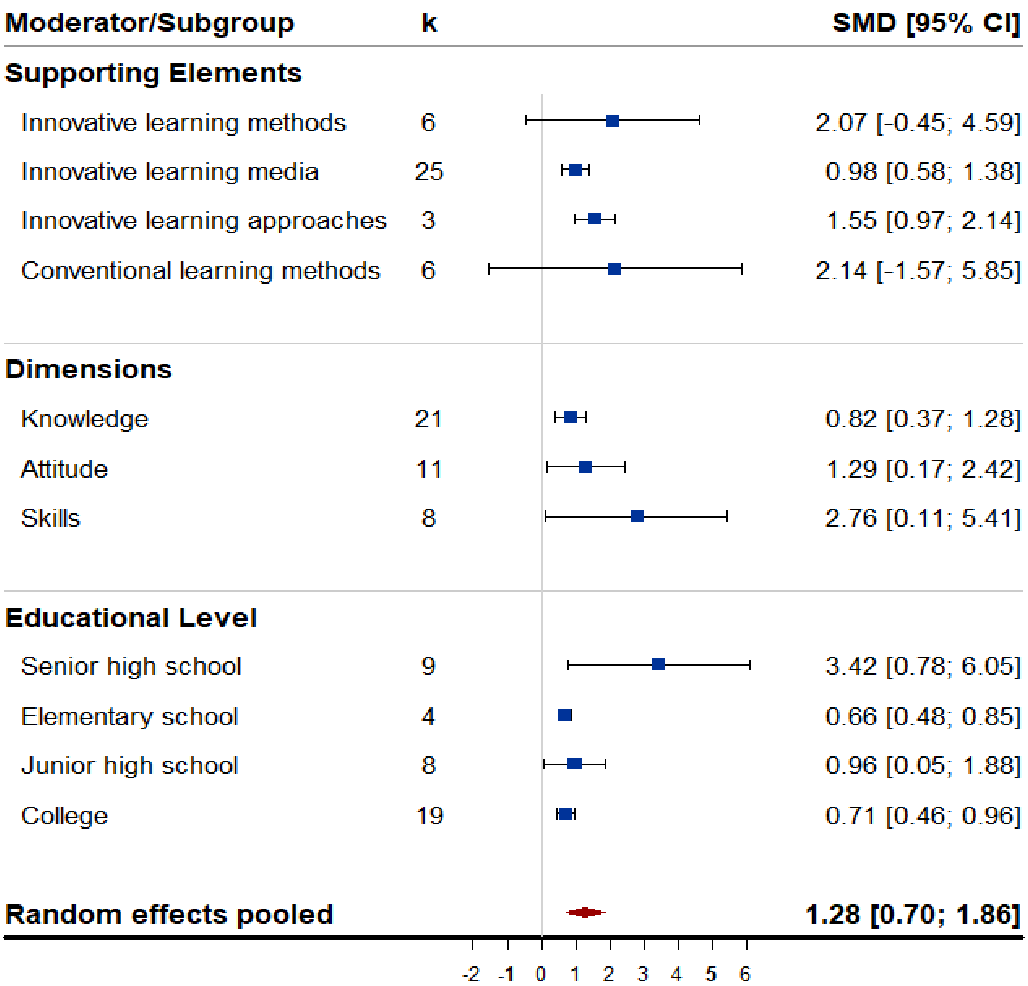

Figure 6. Caterpillar plots for subgroup analysis

Potential for bias and the robustness of analysis results

After conducting subgroup analysis to examine the influence of various moderator variables on the effectiveness of experiential learning, the next step is to analyze the potential for publication bias in the studies analyzed. Publication bias can affect the validity of meta-analysis results (Nair, 2019), so it is important to report potential publication bias to ensure that the findings in this study are not distorted by study selection factors or the presence of specific studies. Thus, the research findings can be interpreted more accurately and comprehensively. Publication bias analysis was performed by visual inspection using funnel plots and statistical testing using Egger's test, the trim-and-fill method, and petterr test. The funnel plot is used to detect asymmetry in the distribution of studies, which may indicate the possibility of publication bias. Figure 7 shows the visualization of study distribution in a funnel plot.

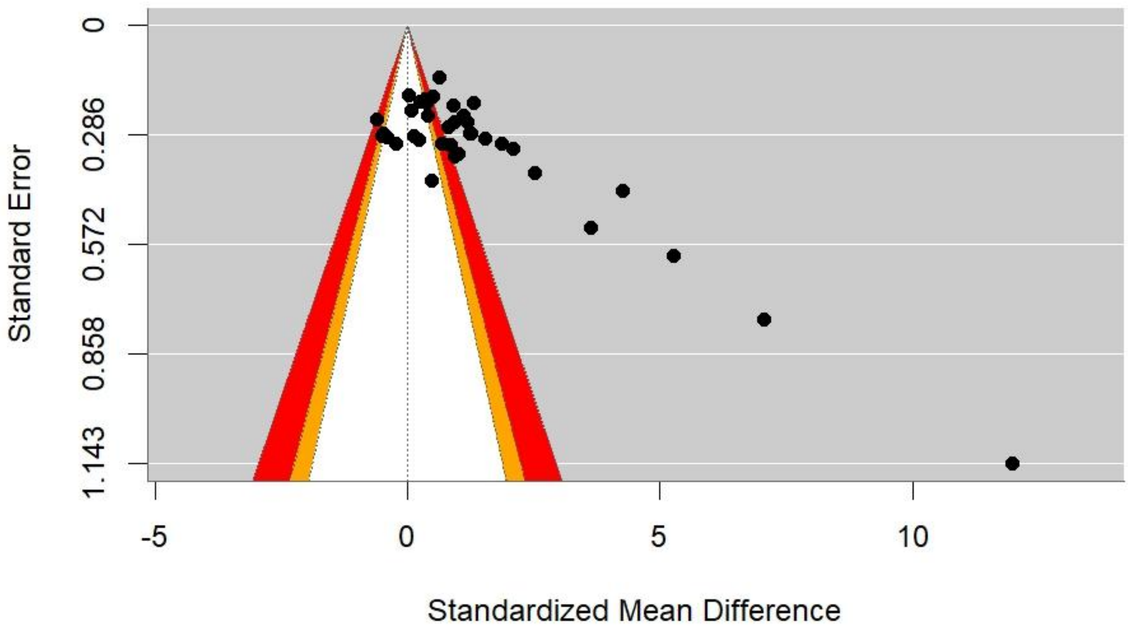

Figure 7. The contour funnel plot

The contour funnel plot in Figure 7 presents the distribution of black dots representing individual studies, with the x-axis showing the standardized mean difference (SMD) and the y-axis showing the standard error of each study effect. The colored areas on this plot distinguish levels of statistical significance: red indicates zones with a p-value < 0.01; orange for p < 0.05; yellow for p < 0.10; while white zones mark non-significant areas (p > 0.10). The distribution pattern on the funnel plot appears asymmetrical, with most data points concentrated on the right side and a few scattered at the bottom of the plot. This condition indicates a possible publication bias, so further analysis is needed to confirm and quantify whether the asymmetry is indeed caused by publication bias or other factors.

The Egger's test is used to measure the degree of asymmetry between effect sizes and standard errors across studies. The test results showed significant asymmetry in the funnel plot (z = 10.99, p < 0.0001), indicating potential publication bias in the analyzed studies. However, the Trim-and-Fill method did not estimate the presence of missing studies on the funnel side (0 studies detected). The estimated pooled effect with a random effects model after Trim-and-Fill correction remained significant (g = 1.31, SE = 0.31, 95% CI [0.70, 1.92], p < 0.0001). These findings indicate that despite some evidence of publication bias, the main results of this meta-analysis remain stable and significant. Additionally, the results of the Peters test also showed no strong indication of publication bias based on the relationship between effect size and the inverse of sample size (t = 0.59, df = 38, p = 0.556; 95% CI [-0.24, 1.27]). Thus, no strong evidence was found to support the existence of publication bias in this analysis.

The presence of publication bias in a meta-analysis does not automatically reduce the validity of the main findings. Aert et al (2019) emphasize that the detection of publication bias cannot be the sole basis for concluding that the results of a meta-analysis are invalid. In practice, it is difficult to determine definitively whether publication bias is truly occurring solely through statistical tests (Afonso et al., 2024). The potential for publication bias in this study could be due to several factors, including the lack of reports on the negative effects of implementing experiential learning, as journals tend to prioritize publishing positive results. Additionally, data source limitations could also be a contributing factor, considering the data in this study was only obtained from the Scopus, ERIC, and Web of Science databases, meaning other relevant literature may not have been fully included.

Opportunities for experiential learning in the future

The findings or results of this study indicate how the experiential learning model significantly impacts the improvement of student learning outcomes, and how it is a potential pedagogical approach to address future educational challenges (Rodriguez & Morant, 2019; Hannon & Temperley, 2022) . This is also supported by the increasing trend of publishing research findings and analyzes related to the application of the experiential learning model. The number of research publications related to the application of experiential learning over the past 15 years shows a significant increase. The data on research trends published in the Scopus database is shown in Figure 8.

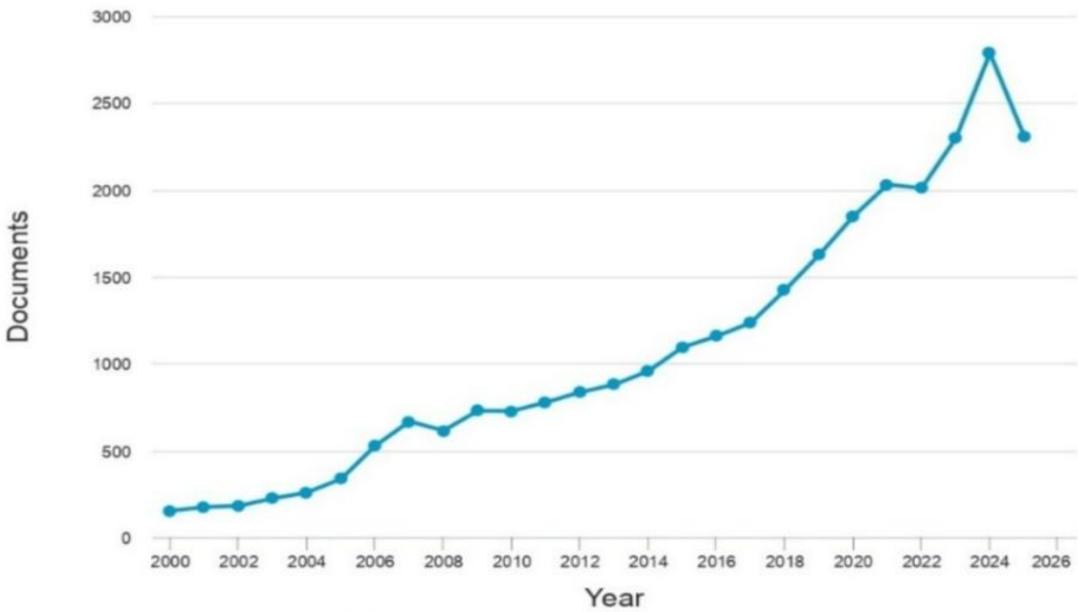

Figure 8. Publication trends on experiential learning

The final subgroup analysis was conducted by grouping studies based on the dimension or form of learning outcomes fostered, including: the knowledge dimension, which encompasses conceptual understanding, critical thinking, computational thinking, and knowledge retention; the skills dimension, which includes process skills, problem-solving, creativity, collaboration, and communication; and the attitudes dimension, which includes environmental awareness, disaster response attitudes, self-efficacy, and motivation

This increasing trend in the number of publications not only reflects the growing academic interest in the experiential learning model but also indicates the increasing need to make experiential learning a core component in supporting the improvement of the quality and effectiveness of learning practices in schools. This finding reinforces the assumption that experiential learning has great potential for continued use in the future, especially in supporting the achievement of a more meaningful, adaptive, and relevant educational process (Sinha, 2023).

In addition to the increasing trend in publications and studies on the experiential learning model, the relevance and opportunities for applying this model in the future are also evident in its alignment with the demands of 21st-century skills, which emphasize critical thinking, creativity, collaboration, and effective communication (Pesha, 2022). These four skills generally represent three domains of basic competence: cognitive, affective, and psychomotor (Singh & Rao, 2024), Based on findings from subgroup analysis, these skills can be effectively developed through experiential learning practices with a combined effect size ranging from 0.82 to 2.76. Thus, the application of this learning is far more appropriate and optimal compared to traditional learning practices that only emphasize the formation of conceptual understanding without significantly supporting the development of other important competencies (Javahery & Bavandi, 2025; Callewaert et al., 2021).

Fulfillment or development of these various dimensions of competence is possible because experiential learning emphasizes several fundamental aspects, such as more contextual learning design (Habib dkk., 2021) , active student involvement (Javahery & Bavandi, 2025) and the application of learned concepts (Wijnen-Meijer et al., 2022). The stages in experiential learning, from concrete experience, reflective observation, and abstract conceptualization to active experimentation, form a unified learning process that optimally promotes the development of various dimensions of student competence or learning outcomes (Hulaikah et al., 2020; Moody, 2025).

Various innovations and cutting-edge technologies, such as artificial intelligence, virtual reality (VR) and augmented reality (AR)-based media, and robotics, are now widely applied in the learning process and have become essential tools that students need to master (Lampropoulos, 2025; Kizilcec, 2024) The experiential learning model shows a high degree of compatibility with various forms of current learning technologies, which is evidenced by its effectiveness when combined with innovative media (Chen dkk., 2025; Hsu dkk., 2022). This is evident from the subgroup analysis results, which show that the use of innovative media yields a high effect size of 0.98, indicating that the effective utilization of innovative media can improve the quality and learning outcomes of students. Similarly, the application of innovative learning methods and approaches currently widely used, which emphasize exploratory and multidisciplinary learning processes such as the STEM approach, also shows compatibility with the experiential learning model (Remington et al., 2023), This is demonstrated by the high effect size values, namely 1.55 for the use of the active approach and 2.07 when the experiential model is compared with the innovative method (Heinrich & Green, 2020). This confirms that this learning model will remain relevant for integration with various innovations and current pedagogical developments, including the use of technology and the formulation of new learning models and methods.

Education in the future requires sustainable, relevant, and adaptive pedagogical approaches and models that can be used at every level of education (Ansari, 2025). Each level of education plays an important role in shaping the quality of students, so the ideal pedagogical approach is one that can be effectively implemented at all levels of education (Jarilkapovich, 2024). This criterion can be met by experiential learning, as this model remains relevant for children of all ages, including those in the concrete operational stage of cognitive development, as well as for students in the formal operational stage (Lebert & Vilarroya, 2024). This is evidenced by the results of subgroup analysis, which show a high effect size across various educational levels, from elementary school to university, ranging from 0.66 to 2.76. Thus, the application of experiential learning has proven effective at various educational levels, providing positive opportunities and prospects for the continued and sustained use of the experiential learning model to facilitate the learning process in the future (Rodriguez & Morant, 2019).

CONCLUSION

The results of this meta-analysis indicate that experiential learning has a significant impact on improving student learning outcomes. The acquisition of a combined effect size with a high category confirms the effectiveness of this learning model in improving various forms and dimensions of student learning outcomes. However, the high level of heterogeneity indicates substantial variance in the context of implementation, subject characteristics, and intervention design across the individual studies. The prediction interval shows a wide range, from -2.56 to 5.18, indicating that the possibility of both positive and negative results remains open for future studies.

The education level variable shows a near-significant effect in moderating the variation in effect sizes across different studies. The results of the subgroup analysis found varied effect sizes, but the overall subgroup category reported positive results. Although there are indications of publication bias through visualization on the funnel plot and the results of Egger's test, testing with the trim-and-fill method and Peter's test shows that the findings of this study remain consistent and valid.

The consistent increase in the number of research publications related to the application of experiential learning, along with its suitability for integration with various innovations and current technologies, its flexibility for implementation across different educational levels, and its ability to accommodate various dimensions or aspects of student learning competencies, make experiential learning remain relevant and necessary to support the learning process in the future. The findings of this research are expected to provide an overview of the effectiveness of implementing experiential learning in improving student learning outcomes, and also serve as a reference for considering, designing, and implementing experiential learning practices.

RECOMMENDATION

This study has limitations because it only collected literature from three databases: Scopus, ERIC, and Web of Science. This raises the possibility that some other relevant studies were not included in the analysis. Therefore, the use of various additional databases is highly recommended to obtain more comprehensive and representative analysis results. Other forms of study, such as systematic literature reviews, are also important to conduct in order to provide a deeper descriptive overview of the latest research and innovations in experiential learning implementation.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Lalu Muhammad Alditia	✓		✓	✓	✓	✓	✓	✓	✓		✓		✓	✓
Andi Suhandi		✓						✓		✓		✓		
Arie Rakhmat Riyadi		✓						✓		✓		✓		
Nurul Fadillah			✓	✓				✓	✓		✓			

Conflict of Interest Statement
Authors state no conflict of interest.

Data Availability
Data is available in the article and/or supporting appendices.

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APPENDIX

Appendix A.

Table A1. Study Characteristic

Author (Year)	Country	Level	Sample (E/C)	Design	Treatment	Dimensions	Timing
Aisyah et al., 2025	Indonesia	Senior HS	35/35	Quasi-experiment	EL with E-river Worksheet	Creativity and environmental care attitude	Immediate
Amico et al., 2020	Italy	Senior HS	23/36	Quasi-experiment	EL with education robot	Material comprehension	Immediate
Chen et al., 2025	China	Elementary	30/32	Quasi-experiment	EL with AR/VR	Material comprehension and learning habits	Immediate
Chiu et al., 2021	Taiwan	College	23/22	Quasi-experiment	EL with AR/VR	Material comprehension, intrinsic/extrinsic motivation, self-efficacy, critical thinking	Immediate
Hsu et al., 2022	Taiwan	Junior HS	25/21	Quasi-experiment	EL with chatbot AI and coding app	Computational thinking	Immediate
Hulaikah et al., 2020	Indonesia	College	60/60	Quasi-experiment	EL	Problem-solving and adversity quotient	Immediate
Indriani & Mercuriani, 2020	Indonesia	Senior HS	27/25	Quasi-experiment	EL with mind map	Material comprehension	Immediate
Lin et al., 2024	Taiwan	College	38/36	Quasi-experiment	EL with chatbot AI	Material comprehension and reflective thinking	Immediate
Liu et al., 2025	USA	Junior HS	21/17	Quasi-experiment	EL with AR/VR	Knowledge resistance and creativity	Immediate
Mardana et al., 2025	Indonesia	Junior HS	56/55	Quasi-experiment	EL	Material comprehension	Immediate
Mariappan, 2025	Malaysia	Elementary	60/60	Quasi-experiment	EL with outdoor learning	Material comprehension	Immediate
Mater et al., 2023	Palestine	Junior HS	30/30	Quasi-experiment	EL with STEAM	Motivation	Immediate
Maulida et al., 2024	Indonesia	Junior HS	25/25	Quasi-experiment	EL with AR/VR	Reasoning and independent learning	Immediate
Nwuba et al., 2022	Nigeria	Senior HS	32/26	Quasi-experiment	EL with mind map	Material comprehension	Immediate
Park et al., 2020	South Korea	College	41/40	Quasi-experiment	EL and web-based learning	Practical skills	Immediate

Author (Year)	Country	Level	Sample (E/C)	Design	Treatment	Dimensions	Timing
Prastawa et al., 2020	Indonesia	Senior HS	20/20	Quasi-experiment	EL with creative industry approach	Entrepreneurial competence	Immediate
Rahim et al., 2022	Malaysia	College	25/23	Quasi-experiment	EL	Self-efficacy and opportunity recognition	Immediate
Sumarni et al., 2020	Indonesia	Senior HS	25/24	Quasi-experiment	EL with field learning	Material comprehension	Immediate
Uzun & Uygun, 2021	Turkey	Junior HS	21/21	Quasi-experiment	EL and simulation-based learning	Problem-solving	Immediate
Wang et al., 2025	China	Elementary	35/35	Quasi-experiment	EL with digital games	Conceptual understanding	Immediate
Zakelj et al., 2024	Slovenia	Elementary	101/130	Quasi-experiment	EL with active learning	Problem-solving	Immediate
Zhong et al., 2025	Hong Kong	College	50/51	Quasi-experiment	EL with digital games	Creativity, critical thinking, and collaboration	Immediate
Zhu et al., 2024	China	College	30/30	Quasi-experiment	EL with digital games	Material comprehension, learning experience, motivation	Immediate

Table A2. Codebook

Variable	Data Type	Example	Brief Definition
Study	Text	"Aisyah et al., 2025_Study 1"	Author name and study identification
n_exp	Numeric	35	Number of subjects in the experimental group
mean_exp	Numeric	26.57	Mean score of the experimental group
sd_exp	Numeric	2.01	Standard deviation of the experimental group
n_ctrl	Numeric	35	Number of subjects in the control group
mean_ctrl	Numeric	16.20	Mean score of the control group
sd_ctrl	Numeric	2.76	Standard deviation of the control group
educational level	Category	"senior high school"	Educational stage where the intervention was implemented

Variable	Data Type	Example	Brief Definition
supporting elements	Category	"innovative learning media"	Main supporting factors/intervention (media, method, approach)
dimensions	Category	"skills", "attitude", "knowledge"	Dimensions of learning outcomes (e.g., knowledge understanding, environmental awareness, creativity)

Appendix B

Table B1. Data information from the study to be calculated Studi dependen Aisyah et al., 2025_Study 1.

Group	Number of Samples	Mean	Standard Deviation
Experimental	35	26.67	2.01
Control	35	16.20	2.76

Table B2. Steps for calculating effect size with Hages' g

Stages	Calculation
Pooled standard deviation	$S_{pooled} = \sqrt{\frac{(n_e - 1)\, Se^2 + (n_c - 1)\, Sc^2}{n_e + n_c}}$ $S_{pooled} = \sqrt{\frac{(34\ x\ 2.01^2) + (34\ x\ 2.01^2)}{68}}$ $= \sqrt{\frac{(34\ x\ 4.0401) + (34\ x\ 7.6176)}{68}}$ $= \sqrt{\frac{137.3634 + 259.1984}{68}}$ $= \sqrt{\frac{396.5618}{68}} = \sqrt{5.8327} = 2.415$
Cohen's d	$d = \frac{\bar{x}_e + \bar{x}_c}{S_{pooled}}$ $d = \frac{26.57 - 16.20}{2.415} = \frac{10.37}{2.415} = 4.29$
Small sample correction	$\mathrm{J} = 1 - \frac{3}{4(n_e + n_c) - 9} = 1 - \frac{3}{4(70) - 9} = 1 - \frac{3}{271} = 0.989$

Hadges' g	$g = d\ x\ J$ $= 4.29\ x\ 0.989$ $= 4.25$
Varians g	$$Var_{(g)} = 1 - \frac{n_1 + n_2}{n_1\ n_2} + \frac{g^2}{2(n_1 + n_2)}$$ $Var_{(g)} = \frac{70}{35\ x\ 35} + \frac{4.25^2}{2\ x\ 70} = \frac{70}{1225} + \frac{18.0625}{140} = 0.0571 + 0.1290 =$ 0.1861

Appendix C

Table C1. Study Structure

Study Name	Year	Number Effect Size	Variabel Clustering
Sumarni et al.	2020	2	Studies
Mariappan	2025	1	Studies
Chen et al.	2025	1	Studies
Mater et al.	2023	2	Studies
Zakelj et al.	2024	1	Studies
Nwuba et al.	2022	1	Studies
Indriani & Mercuriani	2025	1	Studies
Aisyah et al.	2025	2	Studies
Maulida et al.	2024	1	Studies
Wang et al.	2025	1	Studies
Rahim et al.	2022	2	Studies
Liu et al.	2025	2	Studies
Uzun & Uygun	2021	1	Studies
Hsu et al.	2022	1	Studies
Hulaikah et al.	2020	2	Studies
Park et al.	2020	1	Studies
Zhong et al.	2025	4	Studies
Mardana et al.	2025	1	Studies
Prastawa et al.	2020	1	Studies
Lin et al.	2024	2	Studies
Amico et al.	2020	2	Studies
Zhu et al.	2024	3	Studies
Chiu et al.	2021	5	Studies

Table C2. Robust estimate

Metode	Estimate	SE	CI Lower	CI Upper
REML (conventional)	1.309	0.313	0.695	1.923
DL (conventional)	1.153	0.159	0.842	1.465
Winsorized REML	1.102	0.212	0.687	1.517
Robust M-estimator	0.668	0.149	0.376	0.961

Tabel C3. Meta regresion

Predictor / Subgroup	Coefficient (b.r)	SE	t	df	p-value	95% CI Lower	95% CI Upper
Intercept (reference group)	0.72	0.13	5.62	18.0	<0.001	0.45	0.99
Educational Level: elementary school (contrast)	-0.005	0.16	-0.03	4.4	0.978	-0.44	0.43
Educational Level: junior high school	0.22	0.47	0.47	13.0	0.645	-0.80	1.24
Educational Level: senior high school	2.02	1.09	1.86	14.1	0.084	-0.31	4.35
Supporting Elements: innovative learning approaches	0.30	1.09	0.27	4.7	0.798	-2.69	3.29
Supporting Elements: innovative learning media	-0.27	1.07	-0.25	7.0	0.807	-2.81	2.26
Supporting Elements: innovative learning methods	0.44	1.52	0.29	9.6	0.780	-2.98	3.85
Dimensions: Knowledge	-0.36	0.53	-0.67	20.0	0.511	-1.47	0.76
Dimensions: Skills	0.93	1.02	0.91	14.4	0.379	-1.26	3.12

Tabel C4. Leave one out tabel full

Deleted Studies	Pooled g	SE	CI Lower	CI Upper	tau²	I² (%)
Sumarni et al., 2020_Study 1	1.206	0.300	0.617	1.794	3.400	98.03
Sumarni et al., 2020_Study 2	1.160	0.279	0.613	1.707	2.925	97.72
Mariappan, 2025	1.333	0.322	0.701	1.965	3.923	98.21
Chen et al., 2025	1.325	0.323	0.693	1.958	3.935	98.26
Mater et al., 2023_Study 1	1.292	0.322	0.661	1.923	3.915	98.26
Mater et al., 2023_Study 2	1.306	0.323	0.673	1.939	3.938	98.27
Zakelj et al., 2024	1.330	0.323	0.697	1.962	3.930	98.13
Nwuba et al., 2022	1.073	0.225	0.632	1.513	1.868	96.49
Indriani & Mercuriani, 2025	1.356	0.319	0.731	1.981	3.835	98.22
Aisyah et al., 2025_Study 1	1.231	0.310	0.624	1.838	3.614	98.14
Aisyah et al., 2025_Study 2	1.359	0.318	0.736	1.983	3.817	98.20
Maulida et al., 2024	1.357	0.319	0.733	1.981	3.829	98.22
Wang et al., 2025	1.322	0.323	0.689	1.955	3.939	98.26
Rahim et al., 2022_Study 1	1.342	0.321	0.712	1.971	3.897	98.25
Rahim et al., 2022_Study 2	1.355	0.319	0.730	1.980	3.841	98.22
Liu et al., 2025_Study 1	1.322	0.323	0.689	1.954	3.937	98.28
Liu et al., 2025_Study 2	1.251	0.315	0.634	1.868	3.742	98.20
Uzun & Uygun, 2021	1.350	0.320	0.723	1.977	3.863	98.24
Hsu et al., 2022	1.340	0.321	0.710	1.970	3.903	98.25
Hulaikah et al., 2020_Study 1	1.312	0.323	0.679	1.946	3.943	98.23
Hulaikah et al., 2020_Study 2	1.345	0.321	0.715	1.974	3.889	98.19
Park et al., 2020	1.343	0.321	0.714	1.973	3.892	98.22
Zhong et al., 2025_Study 1	1.339	0.322	0.709	1.970	3.906	98.21
Zhong et al., 2025_Study 2	1.318	0.323	0.684	1.951	3.942	98.25
Zhong et al., 2025_Study 3	1.323	0.323	0.690	1.955	3.939	98.23
Zhong et al., 2025_Study 4	1.336	0.322	0.705	1.967	3.916	98.22
Mardana et al., 2025	1.337	0.322	0.706	1.968	3.913	98.21
Prastawa et al., 2020	1.320	0.323	0.687	1.952	3.938	98.28
Lin et al., 2024_Study 1	1.335	0.322	0.704	1.966	3.917	98.24
Lin et al., 2024_Study 2	1.316	0.323	0.682	1.949	3.942	98.26
Amico et al., 2020_Study 1	1.280	0.320	0.652	1.908	3.880	98.26
Amico et al., 2020_Study 2	1.333	0.322	0.702	1.964	3.919	98.28
Zhu et al., 2024_Study 1	1.314	0.323	0.681	1.947	3.942	98.27
Zhu et al., 2024_Study 2	1.313	0.323	0.680	1.946	3.942	98.27
Zhu et al., 2024_Study 3	1.297	0.322	0.665	1.929	3.926	98.27
Chiu et al., 2021_Study 1	1.324	0.323	0.692	1.957	3.935	98.27
Chiu et al., 2021_Study 2	1.324	0.323	0.691	1.957	3.936	98.27
Chiu et al., 2021_Study 3	1.328	0.323	0.696	1.960	3.930	98.27
Chiu et al., 2021_Study 4	1.324	0.323	0.691	1.957	3.936	98.27
Chiu et al., 2021_Study 5	1.325	0.323	0.692	1.957	3.935	98.27