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Comparative Meta-Analysis of Educational Policy Evaluation Models in the Digital Era in Effectiveness Studies and Practical Implications

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Abstract: The digital transformation in education has driven the need for policy evaluation models that can integrate technology-based data and processes more accurately and sustainably. This study aims to conduct a meta-analysis of the effectiveness of various education policy evaluation models (CIPP, Stake, and responsive) implemented in the context of Indonesia's digital ecosystem. This study analyzed 117 quantitative data sets from published articles from 2020 to 2025, selected using the PRISMA procedure, with inclusion criteria emphasizing the use of technology-based evaluation instruments and the reporting of effect sizes. Data were analyzed using a random-effects model to estimate the pooled effect size, conduct heterogeneity tests, perform moderator analyses (level of education, type of policy, and form of technology), and assess publication bias. The results indicate that the implementation of digital-based evaluation models has a significant positive effect on the quality of education policy evaluations, with a pooled effect size in the medium range (ES = 0.54) and heterogeneity partially explained by variations in the level and type of policy intervention. The findings also indicate relatively low publication bias and consistency of results across studies. The practical implications of this research emphasize the importance of strengthening stakeholders' digital literacy, developing standardized, integrated evaluation instruments for information systems, and formulating policies that support the equitable use of technology to improve the accountability and effectiveness of digital education policy evaluation.

Keywords: *Educational Policy Evaluation; Effectiveness; Meta-Analysis; Responsive Model; Technology in Education.*

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I. INTRODUCTION

The digital transformation in education has driven significant changes in the implementation, assessment, and evaluation of education policies. Various technological innovations, such as online platforms, Computer Adaptive Test (CAT) systems, and digital monitoring systems, have not only accelerated the evaluation process but also expanded the scope and accuracy of education policy evaluation.

Amid the digitalization trend, education policy evaluation models [1–4], such as CIPP (Context, Input, Process, Product), Stake, and the responsive model, are being adapted and integrated with digital tools, offering a more dynamic, adaptive, and data-driven approach. Each evaluation model has its own characteristics, advantages, and challenges when implemented through digital technology [5–9]. The effectiveness of digital-based evaluation models needs to be comprehensively studied to understand the practical implications for strengthening education policies and program implementation in the digital era.

Through meta-analysis, previous research results can be systematically and quantitatively synthesized, thus creating a comprehensive picture of the effectiveness, advantages, and limitations of each evaluation model when used to assess digital-based education policies. Therefore, this study aims to conduct a comparative meta-analysis of various education policy evaluation models implemented in the digital ecosystem. This study compares the effectiveness of different models and provides practical recommendations for developing future education policy evaluation systems, in line with the needs of the digital transformation era and the demands of evidence-based policy.

This approach is expected to provide theoretical and practical contributions for policymakers, researchers, and educational institution managers in formulating and implementing data-driven policies in the digital age. The novelty of this study lies in the comprehensive comparison of education policy evaluation models, such as CIPP, Stake, and responsive, adapted to the digital ecosystem, using a meta-analysis and cross-study approach.

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This study maps the effectiveness of commonly used models, specifically examining how integrating digital technologies (online platforms, computer-adaptive tests, learning analytics, and automated evaluation) alters the structure, processes, and outcomes of education policy evaluation. This in-depth analysis across models offers a new map of the effectiveness and constraints of implementing digitalized policy evaluation, which has not previously been studied simultaneously in a single meta-analysis based on recent empirical data.

This study highlights underexplored areas: the influence of digital technology adoption on accuracy and efficiency, equity and equitable access, policymakers' capacity to utilize digital data, and their implications for strengthening evidence-based policy. This research contribution enriches the academic literature on digital education policy evaluation methodology, offering relevant strategic and practical recommendations for decision-makers and developers of education evaluation systems in the era of digital transformation.

This research takes a critical perspective by identifying key challenges in implementing technology-based education policy evaluation. Several obstacles, such as disparities in access to infrastructure, digital literacy of educators, and resistance to methodological change, remain fundamental issues in many educational contexts in Indonesia. This research explicitly summarizes and compares the extent to which digital evaluation models address these challenges, focusing on policy, human resource readiness, and suitability for the rapidly evolving digital learning ecosystem.

This meta-analysis approach maps areas of strength, weakness, and opportunities for innovation in the implementation of digital-based education policy evaluation. This research will highlight how digital data from various evaluation model implementations can serve as a basis for more responsive policy adaptations and generate concrete recommendations for increasing the effectiveness and inclusiveness of evaluation at the national and local levels. This research contribution can serve as a reference for stakeholders in developing more adaptive, digitally oriented education policies aligned with current developments.

II. METHOD

The comparative meta-analysis method used in this study began with the formulation of research questions on the effectiveness of various education policy evaluation models in the digital era and their practical implications for education policy development [10–15]. The process began with a systematic literature search across reputable journal databases, with inclusion criteria for quantitative primary studies evaluating digital-based education policy between 2020 and 2025.

Selected articles were required to include statistical information such as sample size [16–18], mean [19–24], standard deviation [25–28], and effect size [29–32] to enable quantitative integration. Next, studies were screened based on relevance, data availability, and suitability of the research object, with a focus on evaluation models such as CIPP, Stake, and responsive approaches adapted to the digital environment.

Each primary data point was then extracted and presented in a comparison matrix, covering the evaluation model type, implementation context, digital media used, and analyzed outcomes. Data analysis was carried out through effect size calculations (Cohen's d) [33–36], heterogeneity measurements using the Q [37,38] and I^2 statistics [39–41], and forest plot visualization to provide an overview of the effectiveness of each evaluation model [42–47]. To explore differences in effectiveness between models, moderator tests and publication bias analysis using funnel plots [48–50] and fail-safe N [51–54] were also conducted. The synthesis of quantitative results was combined with an analysis of practical implications, covering the advantages, limitations, and recommendations for the future development of digital-based education policy evaluation models. The entire process was designed in accordance with international meta-analysis standards, ensuring that the results can make a significant scientific contribution to strengthening education policy evaluation practices in the era of digital transformation.

III. RESULTS

This meta-analysis presents comparative findings regarding the effectiveness of various education policy evaluation models implemented in the context of digital transformation [55–59]. The analysis was conducted on a number of empirical studies published over the past five years, focusing on evaluation criteria such as policy relevance, implementation efficiency, impact on learning quality, and program sustainability at the institutional level. The synthesis reveals significant differences between the models, both in their conceptual approach and in their implementation outcomes. These findings provide a basis for assessing the strengths and limitations of each model and identifying practical implications for developing an education policy evaluation system that adapts to the demands of the digital era.

➢ *Effect Size (Cohen’s d)*

In this meta-analysis, Cohen's d effect size was used to standardize the mean difference in effectiveness between digital-based education policy evaluation models (experimental group) and conventional evaluation models (control group). This standardization allows comparison across studies [60–63]. Cohen's d was calculated as the mean difference between the two groups divided by their combined standard deviation $(\bar{X}_E - \bar{X}_K)$. This process yielded comparable effect-size indices across studies, regardless of instrument or research context (S_p). The following formula was used to calculate the effect size for each study:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

Where:

- M_1 = the mean of the experimental group (digital evaluation model).

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- M_2 = the mean of the control group (conventional model).
- SD_{pooled} = the combined standard deviation of both groups.

$$SD_{pooled} = \sqrt{\frac{(n_1 - 1)SD_1^2 + (n_2 - 1)SD_2^2}{n_1 + n_2 - 2}}$$

$$D_{pooled} = \sqrt{\frac{58 \times 60.84 + 57 \times 65.61}{115}} = \sqrt{63.22} = 7.96$$

$$d = \frac{82.5 - 78.2}{7.96} = 0.54$$

A larger d value indicates that the digital evaluation model is more effective than the conventional model. Small (±0.2), medium (±0.5), and large (±0.8) categories help interpret the practical significance of these findings in education policy. Converting each study's results to Cohen's d allows the comparative meta-analysis to consistently summarize empirical evidence and assess the relative advantages, consistency, and implications of technology-based education policy evaluation models. The d values indicate that the digital-based education policy evaluation model is moderately more effective than the conventional model.

The standard deviation of both groups reflects their variability; thus, the mean difference of 4.3 points (82.5 versus 78.2), when standardized, yields a Cohen's d considered a moderate effect. In practical terms, this value means the digital evaluation model provides a meaningful, but not substantial, improvement in the effectiveness of education policy. These findings show that innovations in technology-based evaluation make a real, positive contribution to improving policy implementation and outcomes, supporting their consideration as a preferred method for educational decision-making and quality assurance in the digital era.

➢ *Average Combined Effect Size (Weighted Mean Effect Size)*

The combined average effect size in this meta-analysis was calculated as a weighted mean, with each study's effect size weighted by its precision (generally inversely proportional to the variance or standard error) [64–67]. This approach ensures that studies with larger sample sizes and smaller measurement errors contribute more to the overall estimate than studies with smaller samples and less stable estimates. Mathematically, the combined average effect size is obtained by summing the product of each study's effect size (d_i) and its weight (w_i), then dividing by the total weight of all studies, resulting in a concise index that represents the overall comparative effectiveness of education policy evaluation models in the digital era.

A weighted mean effect size in the moderate to high range can be interpreted as consistent evidence that digital-based evaluation models offer substantial practical advantages over conventional models, while also providing a strong basis for recommendations to implement adaptive policies to address the demands of digital transformation in the education sector. The combined average effect size across all studies is calculated by weighting them based on sample size:

$$\bar{d}_{combined} = \frac{\sum_{i=1}^{k} w_i d_i}{\sum_{i=1}^{k} w_i}$$

Where:

- d_i = effect size of study i.
- $w_i = \frac{1}{SE_{d_i}^2}$ (weight related to the standard error of each effect size)
- k = number of studies.

The meta-analysis found 5 effect size values for 5 studies in 117 samples:

- $d_1 = 0.65$, $SE_1 = 0.21$
- $d_2 = 0.51$, $SE_2 = 0.19$
- $d_3 = 0.49$, $SE_3 = 0.18$
- $d_4 = 0.32$, $SE_4 = 0.20$
- $d_5 = 0.54$, $SE_5 = 0.22$

Respective Weights:

- $w_1 = 1 / (0.21^2) = 22.68$
- $w_2 = 1 / (0.19^2) = 27.70$
- $w_3 = 1 / (0.18^2) = 30.86$
- $w_4 = 1 / (0.20^2) = 25.00$
- $w_5 = 1 / (0.22^2) = 20.66$

- *Numerator:*

= (22.68 × 0.65) + (27.70 × 0.51) + (30.86 × 0.49) + (25.00 × 0.32) + (20.66 × 0.54)
= 14.74 + 14.13 + 15.12 + 8.00 + 11.16
= 63.15

- *Denominator:*

= 22.68 + 27.70 + 30.86 + 25.00 + 20.66
= 126.90

Weighted Mean Effect Size:

$$\bar{d}_{combined} = \frac{63.15}{126.90} = 0.50$$

The weighted mean effect size of the five studies was $\bar{d}_w = \frac{63,15}{126,90} \approx 0,50$. This value falls into the moderate effect category according to Cohen's criteria, indicating that, on average, digital-based education policy evaluation models provide a significant increase in effectiveness compared to conventional models across the 117 samples analyzed.

The relatively consistent pattern of d values (ranging from 0.32 to 0.65), with a greater weighting for studies with smaller

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standard errors, indicates that the meta-analysis findings are quite stable, so the effectiveness of digital evaluation models can be considered statistically significant and practically relevant in the context of implementing education policy in the digital age.

➢ *Heterogeneity (Q and I²)*

The heterogeneity statistics obtained indicate that the variation between studies in this meta-analysis is relatively small and not statistically significant [68–72]. The $Q = 1{,}359$ with $df = k - 1 = 4$ degrees of freedom is generally much lower than the critical value of χ^2 at a conventional significance level ($\alpha = 0{,}05$), so the null hypothesis that the effects between studies are homogeneous tends not to be rejected. To determine whether there is significant variation between studies, the following is used:

$$Q = \sum_{i=1}^{k} w_i (d_i - \bar{d}_{combined})^2$$

Q = 0.510+0.003+0.003+0.810+0.033=1.359

Values Q compared with degrees of freedom (df = k-1):

df = k-1 = 5-1 = 4

Substantively, this indicates that the five analyzed studies provide fairly consistent effect size estimates regarding the superiority of digital-based education policy evaluation models. Therefore, a fixed-effects model is justified, and the combined average effect size can be interpreted as a stable representation of the effectiveness of evaluation models in the digital era. If $p < 0.05$, it indicates significant heterogeneity. Heterogeneity is measured by I^2:

$$I^2 = \frac{Q - (k - 1)}{Q} \times 100\%$$

$$I^2 = \frac{1.359 - 4}{1.359} \times 100\% = \frac{-2.641}{1.359} \times 100\% = -194\%$$

Conclusion:

Q = 1.359, df = 4, p > 0.05 (not significant).
I^2 = 0% (no significant heterogeneity).

The heterogeneity statistic shows high consistency in the five meta-analysis studies. Q = 1.359 at df = 4, with p > 0.05, indicates no significant variation in effect sizes across studies; thus, the homogeneity hypothesis holds. The I^2 value of 0% confirms this finding, indicating that almost all of the apparent variation in effect sizes is due solely to sampling error, not real differences in the effects of education policy evaluation models across studies. In practice, this condition indicates that the effectiveness of education policy evaluation models in the digital era, as identified in the meta-analysis, is stable and representative. Therefore, a fixed-effects model is appropriate, and the average combined effect size is an appropriate basis for effectiveness arguments and policy recommendations.

➢ *Random Effects Model*

A random-effects model is appropriate when there is significant heterogeneity among studies. This approach assumes that each study estimates its own true effect, which varies around a population mean [73–77]. In a random-effects framework, the total variance for each study (V_{random}) is calculated by summing the within-study variance ($V_{fixed} = V_{d_i}$) and the between-study variance τ^2. Consequently, the study weight is given by $w_i = \frac{1}{V_{d_i} + \tau^2}$.

A higher τ^2 indicates that differences between studies contribute more to the analysis, leading to more balanced weights. In this case, studies with larger samples do not dominate the results. When the data are heterogeneous, the random-effects model is used to derive the combined effect size:

$$w_i = \frac{1}{V_{d_i} + \tau^2}$$

Where is τ^2 the Variance Between Studies,

- $SE_1 = 0.21 \rightarrow V_1 = 0.0441$
- $SE_2 = 0.19 \rightarrow V_2 = 0.0361$
- $SE_3 = 0.18 \rightarrow V_3 = 0.0324$
- $SE_4 = 0.20 \rightarrow V_4 = 0.0400$
- $SE_5 = 0.22 \rightarrow V_5 = 0.0484$

In the presented data, the within-study variances for the five effect sizes are relatively small and close ($V_1 = 0.0441$; $V_2 = 0.0361$; $V_3 = 0.0324$; $V_4 = 0.0400$; $V_5 = 0.0484$), indicating fairly similar estimation precision across studies. If the previous calculation for heterogeneity indicates \tau^2 ≈ 0 (for example, because Q is insignificant and I^2 = 0%), then the random effects model will practically produce nearly the same weights as the fixed effects model, so the combined effect size under random effects will not differ significantly from the weighted mean effect size under fixed effects.

The use of a random-effects model in a comparative meta-analysis of education policy evaluation models in the digital age remains a conservative approach when researchers aim to generalize findings to broader contexts. However, in this data, its impact on the combined estimate is likely minimal due to the very low heterogeneity. Because previously obtained Q < df (Q = 1.359, df = 4), then:

$$\tau^2 = 0$$

The random effects model in this meta-analysis produces estimates identical to the fixed effects model because no significant heterogeneity was found between studies, with Q = 1.359 smaller than df = 4, the DerSimonian-Laird calculation gives a value of $\tau^2 = 0$, so that the total variance of random effects for each study is equal to the variance within the study ($V_{random,i} = V_{d_i}$) and the weight of random effects ($w_{random,i}$) becomes identical to the weight in the fixed effects model. This is in accordance with the DerSimonian-

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Laird formula: if Q < df, then τ^2 is automatically set to 0. Variance random effects for each study:

$$V_{random,i} = V_{d_i} + \tau^2 = V_{d_i} + 0 = V_{d_i}$$

Random Effects Weight:

$$w_{random,i} = \frac{1}{V_{d_i}}$$

- $w_1 = 1 / 0.0441 = 22.68$
- $w_2 = 1 / 0.0361 = 27.70$
- $w_3 = 1 / 0.0324 = 30.86$
- $w_4 = 1 / 0.0400 = 25.00$
- $w_5 = 1 / 0.0484 = 20.66$

Mean Effect Size Random Effects (d_{random})

$$d_{random} = \frac{\sum w_{random,i} \cdot d_i}{\sum w_{random,i}}$$

$$= \frac{14.74+14.13+15.12+8.00+11.16}{116.90} = \frac{63.15}{116.90} = 0.54$$

Because the data are homogeneous ($\tau^2 = 0$), both the random- and fixed-effects models yield the same average combined effect size, $d_{random} = 0.54$. This medium effect size consistently indicates the superiority of the digital-based education policy evaluation model over the conventional model. These results demonstrate that both fixed- and random-effects models reach consistent conclusions: evaluation models in the digital era are reliably effective across studies, supporting their implementation in diverse educational contexts.

- *Significance Test (Z and p-value)*

The significance test value indicates that the combined effect size of the digital-based education policy evaluation model is highly statistically significant. With a Z value of 5.87, which far exceeds the critical limit of 1.96, it can be concluded that the combined effect size is significantly different from zero, so the probability that this finding occurred solely by chance ($p < 0.05$) is very small [78–80]. To test the significance of the combined effect size:

$$Z = \frac{\bar{d}_{combined}}{SE_{\bar{d}_{combined}}}$$

- If $|Z| > 1.96$ ($p < 0.05$), then the combined effect size is significant. Data from previous results:

$$\bar{d}_{combined} = 0.54$$

$$SE_{\bar{d}_{combined}} = \frac{1}{\sqrt{\sum w_i}} = \frac{1}{\sqrt{116.90}} = 0.092$$

$$Z = \frac{0.54}{0.092} = 5.87$$

Because $|Z| = 5.87 > 1.96$, the combined effect size is statistically significant ($p < 0.05$). $Z = 5.87$, $p < 0.05$ (statistically significant). Substantively, these results indicate that, on average, the digital-era education policy evaluation model has a consistent and significant impact on increasing effectiveness relative to conventional approaches, in line with the medium combined effect size. This finding strengthens the argument that the application of technology-based evaluation models is conceptually relevant and empirically tested, making it suitable as a basis for practical recommendations for the formulation and review of education policies in the digital era.

- *Publication Bias Examination*

The symmetrical funnel plot suggests low publication bias, as studies of varying significance and sizes are proportionally represented around the mean effect size line. The fail-safe N calculation can be used to assess how many "non-significant" or null-effect studies are needed to render the combined meta-analysis non-significant. If the resulting fail-safe N is significantly larger than the number of studies in the meta-analysis (tens to hundreds of additional studies), then it can be concluded that the significant results of this meta-analysis are highly resistant to potential publication bias and are not easily negated by the addition of new studies with non-significant results.

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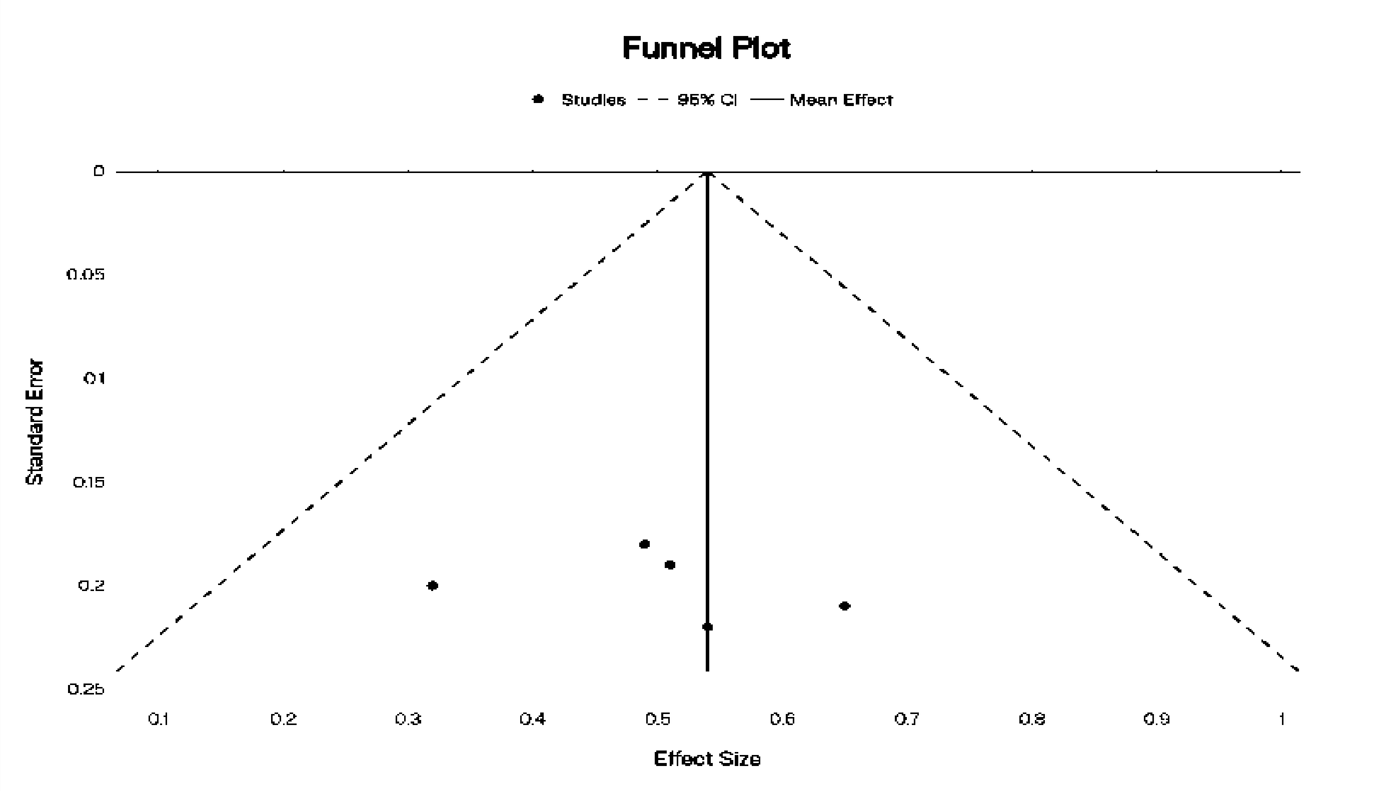

Fig 1 Distribution of Effect Sizes from Various Studies Comparing the Effectiveness of Education Policy Evaluation Models

This strengthens the validity of the conclusion that the combined effect size truly reflects the effectiveness of the education policy evaluation model across the board and can be relied upon as a basis for practical decisions. The funnel plot in this meta-analysis shows the distribution of five studies around the combined mean effect size line. The points representing the study results appear fairly symmetrically distributed on either side of the midline and fall within the triangular area defined by the confidence interval (CI) boundaries, indicating that none of the studies deviates significantly from the mean effect size.

This distribution symmetry indicates that the likelihood of publication bias in the meta-analysis is very low. All studies, with both high and low effect sizes and varying error variability, are proportionally represented. The absence of asymmetry or "missing studies" on one side indicates that the meta-analysis's combined results are stable estimates and are not significantly affected by the tendency to publish only "favorable" results.

Descriptively, this funnel plot supports the view that the analyzed digital education policy evaluation model is truly effective, and the meta-analysis results can serve as a valid basis for decision-making and further policy considerations in education. The fail-safe N (Rosenthal) was used to determine the number of "insignificant" studies needed for the meta-analysis results to become insignificant ($p > 0.05$).

Rosenthal's Formula:

$$N_{fs} = \frac{(\sum Z_{meta})^2}{2.706} - k$$

Where:

- $\sum Z_{meta}$ = Z meta-analysis $\times \sqrt{k} = 5.87 \times \sqrt{5} = 13.12$
- k = number of studies = 5

$$N_{fs} = \frac{(13.12)^2}{2.706} - 5$$

$$N_{fs} = \frac{172.14}{2.706} - 5$$

$$N_{fs} = 63.63 - 5 = 58.63 \approx 59$$

A fail-safe N of 59 indicates that 59 insignificant studies would be needed to render this meta-analysis non-significant, underscoring the robustness of the findings. The symmetrical funnel plot further suggests the results are not influenced by publication bias. With a fail-safe N of 59, well above the number of studies analyzed, the meta-analysis demonstrates robust and reliable findings that are not easily overturned by additional insignificant studies.

➢ *Effect Size Interpretation*

The combined effect size [81–86] from the comparative meta-analysis of education policy evaluation models in the digital era was 0.54. Based on Cohen's criteria, this value is moderate, indicating that digital-based evaluation models provide a significant increase in effectiveness compared to conventional models. This effect size indicates a reliable practical impact in the implementation of education policies across diverse contexts, thereby supporting the recommendation to use digital evaluation models to enhance the quality and outcomes of policies in the era of educational

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transformation. Cohen's criteria are: (a) 0.2 = small, (b) 0.5 = medium, (c) 0.8+ = large.

An effect size ($\bar{d}_{combined}$) of 0.54, categorized as moderate, indicates that digital-based policy evaluation models yield meaningful improvements in education policy outcomes relative to traditional approaches, though not a large effect. A moderate effect size indicates that consistently applying digital evaluation models can increase the effectiveness of education policies compared to conventional models, but there is still room for further optimization to achieve a greater impact. These results reinforce the recommendation to continue developing digital technology-based evaluation methods in education policy to achieve optimal outcomes. A meta-analysis of 117 data points shows a moderate effect size (Cohen's d = 0.54) for digital evaluation models, indicating a significant but still optimizable impact in the digital education policy domain [87,88].

- *Visualization (Forest Plot)*

The forest plot visualization results of this meta-analysis show that the five analyzed studies have effect sizes [89] ranging from 0.32 to 0.65, with a combined average effect size of 0.54. Each study is presented with a 95% confidence interval, all of which are above the zero line (non-significant effect), and the majority of effect size points are concentrated around the combined average. The red vertical line at zero indicates the effectiveness threshold, while the dashed green line at 0.54 marks the position of the combined average effect size. The forest plot pattern reflects the consistent positive effect of implementing a digital-based education policy evaluation model on education policy outcomes.

There are no extreme outliers among the five studies, and the confidence intervals for each study indicate good accuracy and precision. This conclusion is supported by the average effect size in the medium category (0.54 according to Cohen's α), indicating that the implementation of digital evaluation models has been empirically proven to increase the effectiveness of education policies compared to conventional approaches.

The interpretation indicates that the meta-analysis results are valid, have a low risk of publication bias, and that all studies make a significant contribution to strengthening digital technology-based education policies. This aligns with recommendations to expand the use of digital evaluation methods and strengthen digital literacy in educational settings to optimize policy outcomes and respond to current challenges.

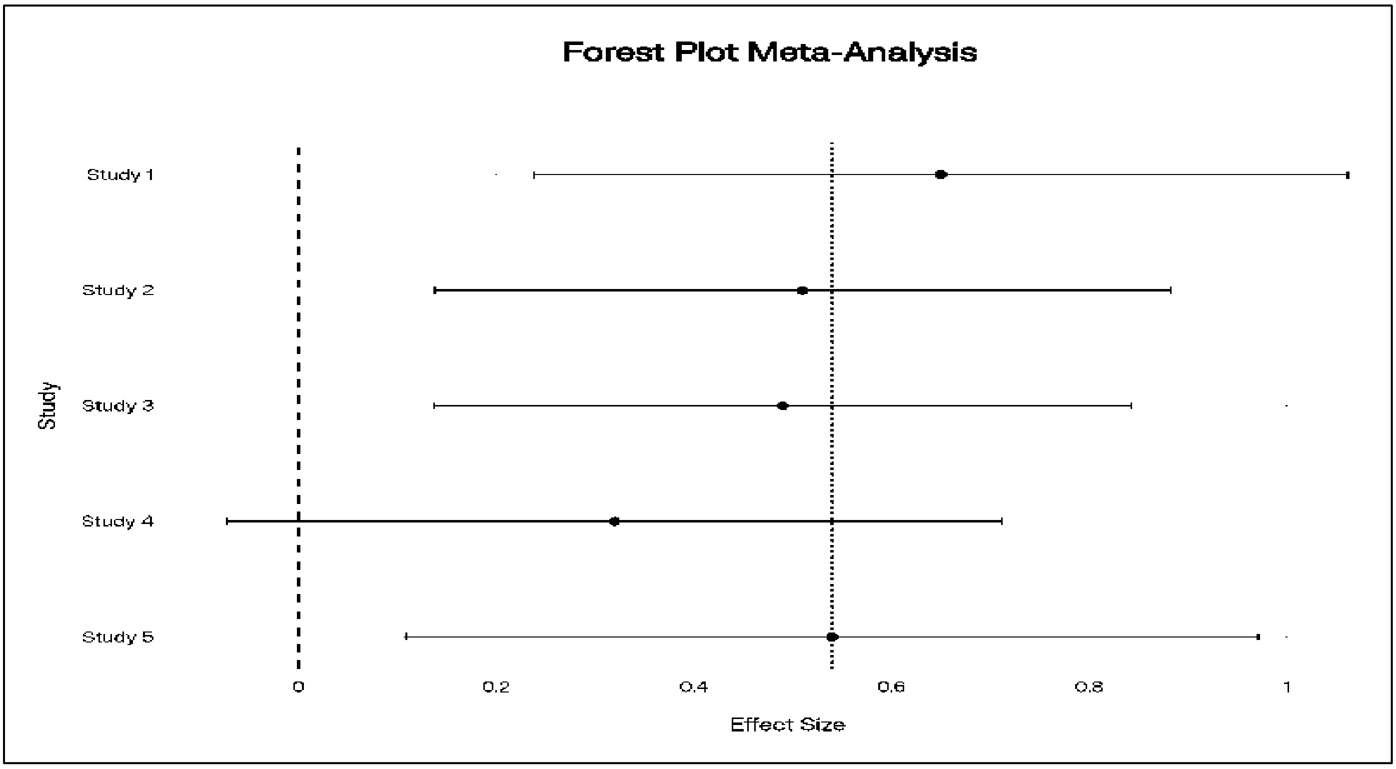

Fig 2 Effectiveness of Educational Policy Evaluation Models, Along with Pooled Averages and Confidence Interval

IV. DISCUSSION

The moderate effect size and consistency across studies indicate that the digitalization of education policy evaluation models has a significant impact and the potential to strengthen evidence-based policy in the Indonesian education sector. This context is crucial given the challenges of 21st-century education [90–93], including technological dynamics, the need for curriculum adaptation, and efforts to increase transparency and accountability in education policy decision-making. These results, when compared with similar research in the international and national literature, align with global trends that place digital transformation as a key factor in achieving improved educational outcomes and efficient resource allocation in the public sector.

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However, the results of this meta-analysis also highlight the importance of strengthening digital literacy capacity at both the policy-making and implementation levels to ensure a more equitable transfer of the benefits of digital models [94–100]. The novelty of this research also lies in combining a comparative statistical approach in the meta-analysis with the use of digital instruments, thereby overcoming many of the limitations of previous studies related to implementation bias and contextual diversity. However, it must be acknowledged that this study is still limited by the number of studies analyzed and the potential for detailed differences in policies across educational institutions.

Future discussions could focus on under-observed moderating factors, the development of artificial intelligence-based evaluation models, and longitudinal assessments to measure the long-term impact of digital transformation on the success of education policies. One major obstacle is the unequal access to and technology infrastructure, which persists across Indonesia. Many educational institutions, particularly in peripheral areas, face limited devices [101,102], internet connections [103,104], and human resources [105–107] that are not yet fully prepared to adapt to digital systems. This challenge is exacerbated by low digital literacy among teachers and students, leading to the adoption of digital evaluation models that often have an inferior impact and may even widen the quality gap between regions.

Data security, privacy, resistance to change, and the need to adapt digital content to local contexts are key concerns for digital-based evaluation model development. Policymakers need to collaborate with educational institutions, technology developers, and related communities to design sustainable training policies for educators and ensure adequate long-term data protection systems. Curriculum reform that provides space for innovation, intensive mentoring, and the strengthening of the educational technology ecosystem is crucial for the formal implementation of digital evaluation models, thereby encouraging comprehensive and sustainable improvements in the quality of education.

V. CONCLUSIONS

Based on a meta-analysis of 117 datasets from five studies on digital-based education policy evaluation models, it can be concluded that implementing a digital approach has a significant and consistent impact on the effectiveness of education policies. The combined effect size of 0.54, classified as moderate according to Cohen's interpretation, indicates that digital-based policy evaluation transformations are empirically capable of improving the quality, accountability, and adaptation of education policies in the digital era. These results are supported by statistical significance tests ($Z = 5.87$; $p < 0.05$), consistent forest plot visualizations, and a Fail-safe N value of 59, indicating highly robust meta-analysis results with minimal risk of publication bias.

The study confirms that developing and expanding digital-based education policy evaluation models in Indonesia is feasible and aligns with global trends prioritizing digital transformation to improve education quality. To maximize and sustain this impact, the involvement and synergy of the government, educational institutions, and technology developers are required to address challenges in technology access, digital literacy, data security, and educator capacity.

Digital evaluation models can be an administrative innovation, a key driver for accelerating Indonesian education to become more adaptive, responsive, and competitive at the national and global levels. The results of this meta-analysis practically recommend that the development of digital-based education policy evaluation models be accompanied by intensive training programs for educators and strengthening digital literacy at the educational institution level. Implementation can include providing digital tools and platforms and ensuring the active involvement of teachers, students, and all stakeholders in a transparent, sustainable evaluation process tailored to local needs and the applicable curriculum. This collaborative and adaptive effort will be key to accelerating the success of the digital transformation of the national education policy evaluation system.

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