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Abstract

The engineering design process (EDP) is an innovative problem-solving approach used to develop effective solutions and products. While numerous studies have explored its implementation and potential effects, its impact on cognitive learning outcomes remains unclear. Thus, this current study aimed to evaluate the effectiveness of EDP. Meta-analytic findings from 17 studies with 29 valid datasets published from 2015 to 2024 revealed an upper-medium effect on cognitive learning performance (g = 0.70, p < .001). Additionally, geographic region, group selection, grade level, EDP model, and EDP skills had moderating effects. Furthermore, subgroup analysis indicated that EDP implementation was more effective under the following conditions: (1) increased exposure to EDP, (2) smaller and (3) randomized class sizes (1-30 and 31-50 students), (4) Asian (5) high school students, and (6) the use of EDP models such as DDCTPE *(Define the Problem, Decide Possible Solutions, Create the Design, Test, Present, Evaluate)* and AIPCTI *(Ask, Imagine, Plan, Create, Test, Improve)*. Overall, the engineering design process significantly enhanced core engineering knowledge and practice, as well as students' cognition and thinking.

Introduction

The engineering design process (EDP) is an approach utilized in problem-solving. In this pedagogy, learners acquire engineering-related practices and skills. According to TeachEngineering (2023) from the University of Colorado, EDP has a series of steps that guide students in solving problems. Additionally, teamwork and design are the key components of the strategy. The steps of the EDP involve defining the problem, conducting research, generating ideas, selecting the optimal solution, developing and testing prototypes, refining the design, and effectively communicating the results (Hafiz & Ayop, 2019). Similarly, Tipmontiane and Williams (2021) highlighted that the steps of the engineering design process are iterative and creative learning processes that integrate interdisciplinary concepts from science, mathematics, and technology. Incorporating the engineering design process (EDP) into the curriculum benefits students. Capobianco et al. (2014) reported that engineering design-based science in elementary schools promotes student participation, sustains learners' interest, and enhances their self-concept in engineering and science. Meanwhile, Goktepe Yildiz and Ozdemir (2018) reported that EDP activities positively enhance students' spatial abilities. Additionally, Bunprom et al. (2019) observed the development of engineering design process skills among students.

Sudrajat et al. (2023) examine the impact of the engineering design process on high school students' creativity. Their findings reveal that EDP improves students' creative thinking. Additionally, they identify a significant difference between students' creative thinking skills and their creativity in product development. Radloff et al. (2019) report an increase in understanding of students utilizing engineering design in undergraduate biology in which students design models of the composting process. On the other hand, LaKose (2015) argues that although the use of the engineering design process (EDP) is beneficial, it still requires refinement and remains in its early stages. The author also presents EDP-oriented learning activities aligned with the Next Generation Science Standards (NGSS) in the United States.

Moreover, Selcen Guzey et al. (2016) describe the impact of design-based STEM curriculum integration on students' achievement in engineering, mathematics, and science. The authors argue that the engineering design process (EDP) and its practices are relatively new to many teachers, making implementation challenging. Their study documents that EDP integration has varying effects across race and gender, which can either reduce or exacerbate achievement gaps in engineering among student subgroups, depending on the outcomes. Additionally, teacher-related factors, such as the quality of engineering-focused science units and the effectiveness of engineering instruction, significantly predict student achievement in engineering. These results require strengthening the professional development of teachers to enhance the implementation of EDP in different contexts. Overall, the previous studies and literature on the engineering design processes suggest this educational approach is particularly beneficial for STEM students and improves learning outcomes.

On the other hand, the systematic literature review of Winarno et al. (2020) on empirical research on the engineering design process (EDP) in science education from 2010 to 2020 reports that projects are commonly used to implement the EDP, varying according to the content being discussed. Authors highlight that the EDP enhances cognitive skills, develops procedural skills, and fosters positive attitudes. Additionally, they emphasize that the EDP is an emerging trend in science education, highlighting the need for further research to provide essential data for policy decisions involving teachers, students, and other stakeholders. This study focuses on summarizing the effects of the engineering design process (EDP) through a meta-analysis approach, aiming to provide insights into its impacts and inform policy development related to the approach. Lastly, the research offers empirical data on the significance of EDP implementation in the classroom.

Meta-analysis studies show that design thinking (DT), a broader approach than EDP, positively impacts student performance and educational outcomes (Yoon, 2023; Yu et al., 2024). Yu and colleagues report that out of 25 articles, DT has a positive effect on student learning ($r = 0.436$, $p < 0.001$). They also identify several moderating factors such as learning outcome, treatment duration, grade level, DT model, and region. DT instruction is more effective when: (1) class size is ≤30, (2) applied to multidisciplinary contexts, and (3) duration is ≥3 months. Meanwhile, Yoon utilizes 21 studies and reports an overall effect size of 0.469 for design thinking (DT), interpreting this as a moderate effect size. The results confirm that DT interventions are effective for better educational outcomes. Notably, the researcher finds that DT interventions have the largest effect on academic achievement. Overall, these results emphasize the ongoing deficiency of meta-analysis studies on the effects of the engineering design process (EDP) on the cognitive ability of students, indicating a gap in research that could provide valuable insights for educational policies and improving educational practices, including better learning outcomes.

Interestingly, the work-in-progress meta-analysis by Fidai et al. (2020) on the engineering design process (EDP) in science and mathematics provides initial empirical data on its effects. The researchers find that articles published during and after 2018 reveal a significant Cohen's *d* effect size of 0.31 (CI = 0.18, 0.44) on students' science and mathematics achievement. The findings suggest that implementing the EDP enhances students' learning experiences and improves their academic achievement in science and mathematics. Despite these results, the study has limitations, such as the inclusion of only six (6) studies and 18 data sets and its focus on publications from 2018 to 2019. Since this study is considered a work in progress, it is important to note that future research may revise the paper to include new publications related to EDP. Similarly, the study of Panergayo and Prudente (2024) also reports a large effect size (g = 1.530) on enhancing scientific creativity using the engineering design process model in STEM education from six articles published between 2015 and 2023. Moreover, the authors considered this as the maximum effect size compared to STEAM design (0.696) and design thinking (0.869). In contrast, the current inquiry utilizes peer-reviewed studies from 2015 to 2024, where EDP is used to enhance the cognitive ability or performance of the students. Further, this research attempts to cover EDP in various disciplines, not just STEM and determines the between-group effects using different moderators. Notably, studies on the impacts of the engineering design process (EDP) on student cognitive performance, in general, remain unanswered, and this drives the current investigation to evaluate the various empirical research on the effectiveness of EDP.

Research Questions

Generally, this investigation aims to determine the effects of the engineering design process (EDP) on student cognitive performance. Specifically, this meta-analysis sought to answer the following questions:

1. What are the characteristics of the studies included in the meta-analysis?
2. What is the effectiveness of the engineering design process (EDP) in enhancing cognitive learning performance?
3. Was there a significant difference in the effect sizes according to the moderators such as location, duration, class size, group selection, grade level, EDP model, and engineering design process skills?

Methodology

This investigation employed a meta-analysis method to determine the effects of the engineering design process on students' cognitive performance. According to Riffenburgh (2012), a meta-analysis is a systematic method of combining multiple studies to generate results with a larger sample size. Likewise, a meta-analysis yields overall statistics, including the confidence interval, that summarize the effectiveness of the experimental intervention compared to a comparator intervention. The advantages of this method include improving precision, answering questions not addressed in individual studies, resolving controversies from seemingly conflicting results, and generating new hypotheses (Higgins & Thomas, 2019).

The meta-analysis procedure in this investigation generally follows the eight-step practical guide outlined by Hansen et al. (2021). These steps include: (1) defining the research questions; (2) conducting the literature search, including developing a search strategy, establishing inclusion criteria, and acquiring the sample; (3) selecting the effect size measure, which involves determining the appropriate type of effect size and converting effect sizes to a common metric; (4) choosing the analytical method, such as univariate meta-analysis, meta-regression analysis, meta-analytic structural equation modeling, or qualitative meta-analysis; (5) selecting the appropriate software; (6) coding effect sizes using a coding sheet, including moderator or control variables; (7) assessing outliers and publication bias, including choosing between fixed-effects and random-effects models; and (8) reporting the results in the article.

Search Strategy

The studies included in this meta-analysis were collected between January 5 to 27, 2025, from reputable databases and indexing sites such as DOAJ, ERIC, ACI, Dimensions, Lens, Google Scholar, and ScienceDirect. ResearchGate and Semantic Scholar were also used to identify relevant publications. These databases and resources contain high-quality scientific publications in various international journals. Utilizing multiple databases and search engines ensured a comprehensive search for articles to include in the analysis. This procedure is similar to the process of Yu et al. (2024) by employing different sources to reduce the literature search bias. The systematic search used the keywords "engineering design" and "engineering design process." All included documents were peer-reviewed to ensure the quality of the meta-analysis.

Publication Selection

The study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The systematic search flow for identifying studies related to the engineering design process is illustrated in Figure 1. Moreover, to guide the process of selecting the articles the following criteria are followed:

a. The study must report on the implementation of the engineering design process and its impact on cognitive learning variables;
b. The investigation utilized an experimental or quasi-experimental research design; where the experimental group received the EDP intervention;
c. The article must provide necessary and sufficient quantitative data for the calculation of the effect size;
d. Peer-reviewed and published in the English language.

Initially, 2,773 journal articles were identified from all databases and 52 reports from other sources. After excluding duplicate articles and removing others based on title and abstract screening, the number was reduced to 2,208 articles. Further filtering led to the exclusion of articles not focused on education, resulting in 419 articles for retrieval. Additionally, through other identification methods, three articles were not recovered, leaving 49 articles for appraisal. From the databases, 43 articles could not be retrieved, and only 376 were assessed for final inclusion. After excluding articles unrelated to the engineering design process, lacking variables for cognitive learning, without control groups, or with insufficient data for effect size calculation, only 17 studies were included in the meta-analysis.

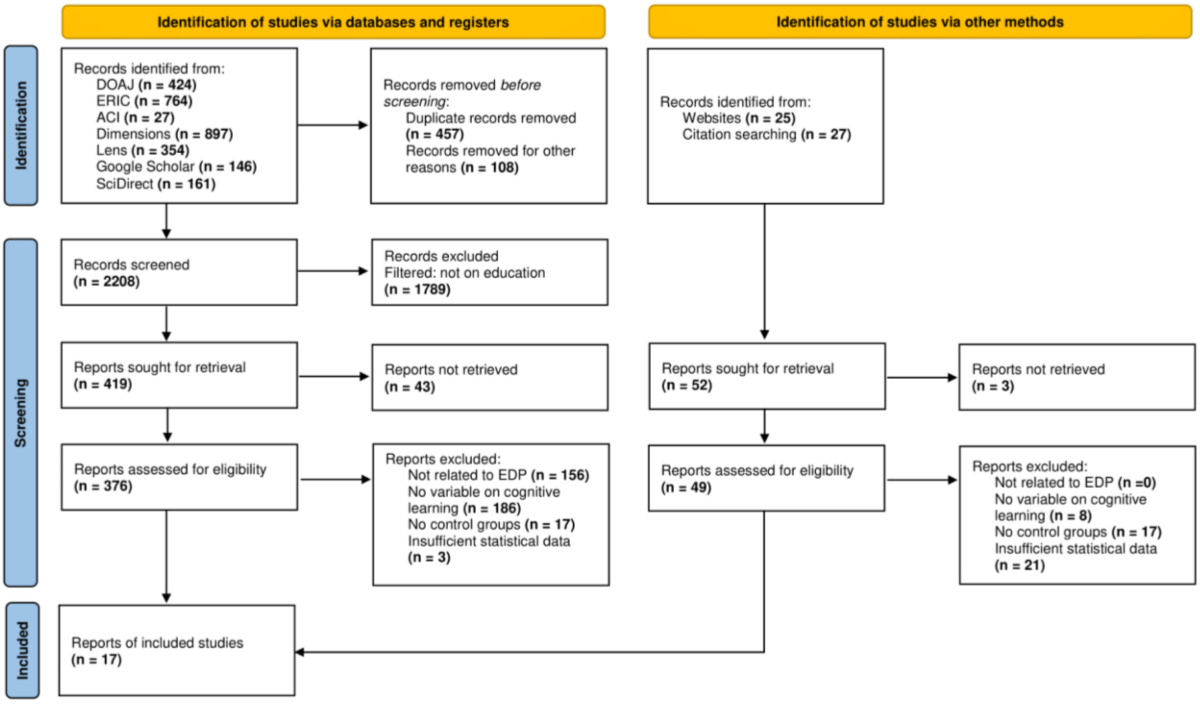

Figure 1. PRISMA Flow Diagram Search of EDP from Databases, Registers, and Other Sources

Risk of Bias Assessment and Quality of the Studies

According to De Cassai et al. (2023), assessing the risk of bias is mandatory when conducting a meta-analysis, as it provides an overview of the quality of the studies from which data are extracted. In this meta-analysis, the quality and risk of bias assessment of the 17 identified articles were evaluated using the domains from the JBI Critical Appraisal Tool for Quasi-Experimental Studies 2023. The checklist includes the following risk of bias domains: (1) bias related to temporal precedence, (2) selection, and allocation, (3) confounding factors, (4) administration of intervention/exposure, (5) assessment, detection, and measurement of outcomes, including the (6) bias related to participant retention (Barker et al., 2024). Additionally, statistical validity was also examined. Moreover, to visualize the risk-of-bias assessment figures, the *robvis* tool by McGuinness and Higgins (2020) was employed using the generic template for datasets.

Figures 2 and 3 present the risk of bias assessment results based on the author's appraisal. It is noted that all studies exhibit a low risk of bias related to temporal precedence, indicating that the articles clearly identified which variable was manipulated as the potential cause. Next is the bias related to selection and allocation, which assesses whether control groups were present. Moreover, the bias related to the administration of intervention or exposure is considered to be a low risk of bias. This domain is necessary to check because to attribute the observed effect to the cause, it is assumed that participant characteristics are balanced between groups, and there should be no other differences in the treatments or care received, aside from the manipulated variable. Moreover, a low risk of bias is documented related to the assessment, detection, and measurement of outcomes. This domain evaluates the use of reliable measurement tools or scales, the process of assessment, the adequacy of statistical power, and potential violations of assumptions in statistical tests. Further, a low risk of bias is also reported on bias related to participant retention. This domain assesses participant retention by checking whether follow-up was conducted. If some students drop out or stop participating in the study, it is important to report the number of students lost to follow-up, the reasons for their withdrawal, and whether this affected the study's outcomes. Conversely, the author reports that nine (9) studies lack information regarding bias related to confounding factors. This domain assesses the baseline data or characteristics of participants in each comparison group. Notably, internal validity may be compromised if there are significant differences in participant characteristics between the groups being compared. Overall, the appraisal of the included studies yielded a low risk of bias, this ensures the reliability of the effect size computation in the meta-analysis and could be used to inform policy decisions.

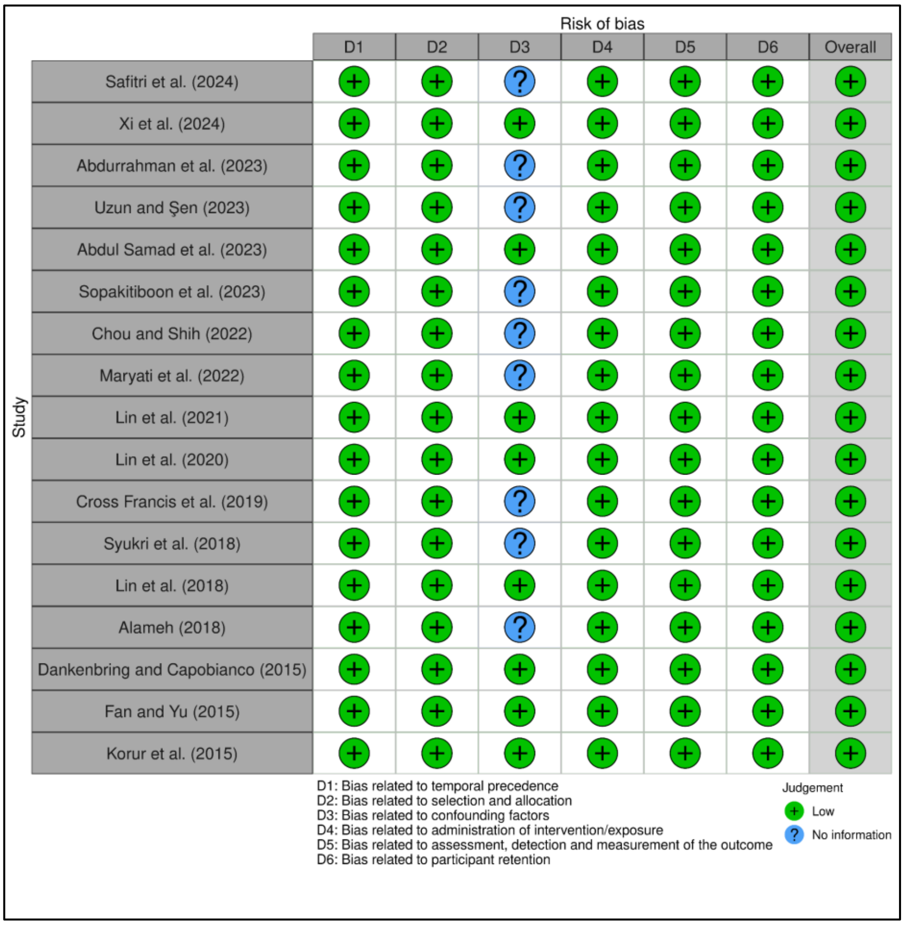

Figure 2. Risk of Bias Assessment Results of the Individual Studies

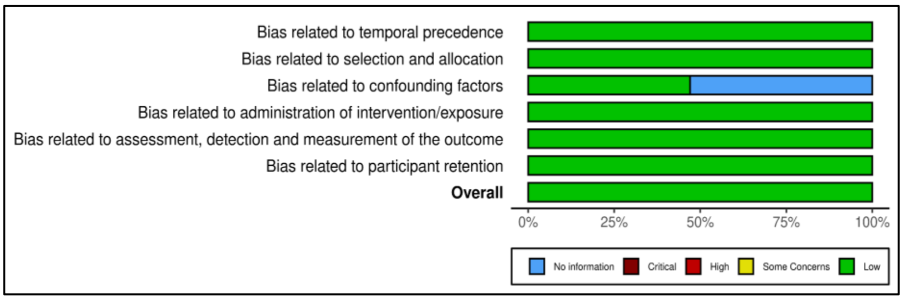

Figure 3. Overall Risk of Bias Assessment of the Studies included in the Meta-analysis

Data Extraction and Coding the Potential Moderators

The researcher used a meta-analysis matrix to extract data from the 17 articles, including the characteristics of each study such as document type, journal source, country, EDP implementation, journal ranking such as Scimago Journal & Country Rank (SJR) or Science and Technology Index (Sinta), citations, cognitive variables, and the statistical data for effect size computation. Additionally, potential moderators or factors that may influence the effects of the engineering design process (EDP) were also extracted.

1. Geographic Region - this moderator refers to the study's location, categorized as *East Asia, West Asia, Southeast Asia,* and the *Midwest USA*.
2. Duration - this factor refers to the length of time of implementation of the engineering design process and is categorized as *<3 weeks, 4-6 weeks, 7-9 weeks,* and *>10 weeks*.
3. Class Size - this moderator refers to the number of students in the class where the EDP is implemented, categorized as *1-30, 31-50, 51-100,* and *>100*.
4. Group Selection - this factor refers to the process by which researchers assign participants to either the control or experimental group, categorized as *randomized* or *nonrandomized*.
5. Grade Level - this moderator refers to the educational stage of the participants, categorized as *preschool (aged 2-5), elementary (aged 5-10), middle school (aged 11-13), high school (aged 14-18),* and *university level*.
6. EDP Model - refers to the specific stages of various engineering design process models. Four models were identified in the study: AIPCTI *(Ask, Imagine, Plan, Create, Test, Improve)*, DDCTPE *(Define the Problem, Decide Possible Solutions, Create the Design, Test, Present, Evaluate)*, EDIPT *(Empathize, Define, Ideate, Prototype, Test)*, and CTC *(Copy, Tinker, Create)*.
7. EDP Skills - refers to engineering design process skills. Since this meta-analysis study focuses on cognitive performance, variables were coded into two broad categories based on the domain classifications of EDP skills by Abdulwahed and Hasna (2016): *Core Engineering Knowledge and Practice*, and the skills related to *Cognition and Thinking*.

Data Analysis

The study utilized the mean, standard deviation, and sample size, with the bias-corrected standardized mean difference (Hedges' *g*) as the effect size measure. Hedges' *g* can be applied to both large and small samples, eliminating the need to switch between Hedges' *g* and Cohen's *d* in the analysis that includes studies with varying sample sizes (Chalmers & Altman, 1995, as cited in Turner & Bernard, 2006). Additionally, to address variations in effect sizes across studies, conversions were performed using Wilson's (2023) online effect size calculator, this process is based on the meta-analysis guide of Hansen et al. (2021) using the standard books of Lipsey and Wilson (2001) and Borenstein et al. (2009).

Furthermore, JASP 0.19.3 was used to determine the effects of the engineering design process. The statistical software generates statistics, figures, and tables, including the pooled effect size displayed in the forest plot, as well as the funnel plot and publication bias assessment. Meanwhile, subgroup analysis was performed in SPSS 30

(172) to determine the difference in the mean effect size of factors (moderators) and the direction of difference between subgroups (Çikrıkci, 2016). Lastly, the effect size was interpreted using Sawilowsky's (2009) revised rules of thumb: g = 0.01 (very small), g = 0.2 (small), g = 0.5 (medium), g = 0.8 (large), g = 1.2 (very large), and g = 2.0 (huge).

Results and Discussion

This section presents the characteristics of the studies included in the meta-analysis and examines the effects of the engineering design process on students' cognitive learning performance including the difference in the effect size of the identified potential moderators.

Characteristics of the Studies included in the Meta-analysis

Table 1 presents the features of each study included in the analysis. A total of 17 documents were considered in the meta-analysis, consisting mostly of original research articles, along with one thesis and one conference paper. Publications on the engineering design process (EDP) originated from eight countries: China, Indonesia, Lebanon, Malaysia, Taiwan, Thailand, Turkey, and the United States. Notably, these articles were published from year 2015 to 2024. Moreover, data from the Scimago Journal & Country Rank and Sinta Journal Rank indicate that most studies were published in reputable journals and universities, and indexed in various databases. The studies by Fan and Yu (2015) and Lin et al. (2021) received the highest number of citations, with 294 and 214 citations, respectively. Furthermore, the EDP was implemented as an intervention in experimental groups across different educational levels, from preschool to university. All studies examined the effects of EDP on cognitive learning outcomes, including critical thinking ability (Safitri et al., 2024), computational thinking (Abdul Samad et al., 2023), interdisciplinary knowledge (Cross Francis et al., 2019), and learning gains (Dankenbring & Capobianco, 2015).

Table 1. Characteristics of Studies included in Meta-analysis

Authors	Type	Journal	Country	EDP Implemented	Ranking (SJR/ Sinta)	Citations
Safitri et al. (2024)	Article	Jurnal Penelitian Pendidikan IPA	Indonesia	STEM-based Engineering Design Process	Sinta 2	1
Xi et al. (2024)	Article	Educational Technology Research and Development	China	EDP Conceive Design Implement Operate (CDIO)	Q1	1
Abdurrahman et al. (2023)	Article	Heliyon	Indonesia	STEM-PBL Integrated Engineering Design Process	Q1	45

Authors	Type	Journal	Country	EDP Implemented	Ranking (SJR/ Sinta)	Citations
Uzun and Şen (2023)	Article	Journal of Pedagogical Research	Turkey	STEM-based activities Engineering/ Design	Q2	13
Abdul Samad et al. (2023)	Article	International Journal of Educational Methodology	Malaysia	CThink4CS2 Module with Engineering Design Process (EDP)	Q3	1
Sopakitiboon et al. (2023)	Article	International Journal of Engineering Pedagogy	Thailand	New-product creativity (NPC) through the engineering design process (EDP)	Q2	2
Chou and Shih (2022)	Conference Paper	Innovative Technologies and Learning	Taiwan	Engineering design thinking in robot projects	-	3
Maryati et al. (2022)	Article	Scientiae Educatia: Jurnal Pendidikan Sains	Indonesia	Arduino-based engineering design process (EDP)	Sinta 3	4
Lin et al. (2021)	Article	International Journal of STEM Education	Taiwan	EDP & STEM project-based learning	Q1	214
Lin et al. (2020)	Article	Early Education and Development	China	Inquiry-based science and engineering (IBSE) program	Q1	72
Cross Francis et al. (2019)	Article	School Science and Mathematics	United States	Pre-engineering program: A Workplace Simulation Project	Q2	6
Syukri et al. (2018)	Article	Jurnal Pendidikan IPA Indonesia	Indonesia	Integration of the engineering design process in the module	Q3/ Sinta 1	79
Lin et al. (2018)	Article	Eurasia Journal of Mathematics, Science and Technology Education	Taiwan	EDP 3D Printing Technology in STEM/ Project-Based Learning Activities	Q2	57

Authors	Type	Journal	Country	EDP Implemented	Ranking (SJR/ Sinta)	Citations
Alameh (2018)	Thesis	American University of Beirut	Lebanon	Science and Engineering Practices in Biology	-	5
Dankenbring and Capobianco (2015)	Article	International Journal of Science and Mathematics Education	United States	EDP-based science task	Q1	57
Fan and Yu (2015)	Article	International Journal of Technology and Design Education	Taiwan	Technological/ engineering design-based module	Q1	294
Korur et al. (2015)	Article	International Journal of Science and Mathematics Education	Turkey	Toy Crane Design-Based Learning on Simple Machines	Q1	28

Effectiveness of the Engineering Design Process (EDP) in Enhancing Cognitive Learning Performance

A total of 17 studies with 29 valid study datasets were included in the meta-analysis. According to Borenstein et al. (2009), when a researcher aims to combine data from different studies conducted independently by other scholars, all investigations are unlikely to be identical or functionally equivalent. Differences in respondents and interventions may influence the results, making it inappropriate to assume a common effect size. Therefore, the random effects model is more justified than the fixed effects model in such cases. Using this premise, this meta-analysis utilized a random effects model to determine the effects of the engineering design process on students' cognitive learning performance. Table 2 presents the meta-analytic results examining the effectiveness of the EDP. A pooled effect size (Hedges' g) of 0.70 was calculated from 29 independent datasets (k = 29), indicating an upper-medium positive effect of the engineering design process on cognitive learning outcomes, as represented by the diamond in the forest plot in Figure 4. Likewise, this effect was statistically significant ($Z = 6.774$, $p < .001$), with a 95% confidence interval (CI) ranging from 0.499 to 0.905. Notably, this result is consistent with the work-in-progress meta-analysis performed by Fidai et al. (2020), which found that the engineering design process affected students' science and mathematics achievement, with a Cohen's d value of 0.31, indicating a small effect size based on six studies with 18 datasets. Similarly, Panergayo and Prudente (2024) reported the effects of the engineering design process from six studies, with a Hedges' g value of 1.530, indicating a large effect size on scientific creative thinking. Overall, the results of the current meta-analysis corroborate previous findings, confirming that the engineering design process (EDP) has positive effects on learning outcomes, particularly in cognitive learning performance.

Table 2. The Pooled Effect Size of the Engineering Design Process and the Residual Heterogeneity Statistics

k	***Hedges'g***	***SE***	***Z***	***p***	***95% CI (Lower)***	***95% CI (Upper)***
29	0.70	0.104	6.774	<.001	0.499	0.905
τ	***$τ^2$***	***I^2***	***H^2***	***df***	***Q***	***p***
0.473	0.224	79.838%	4.960	28	94.765	<.001

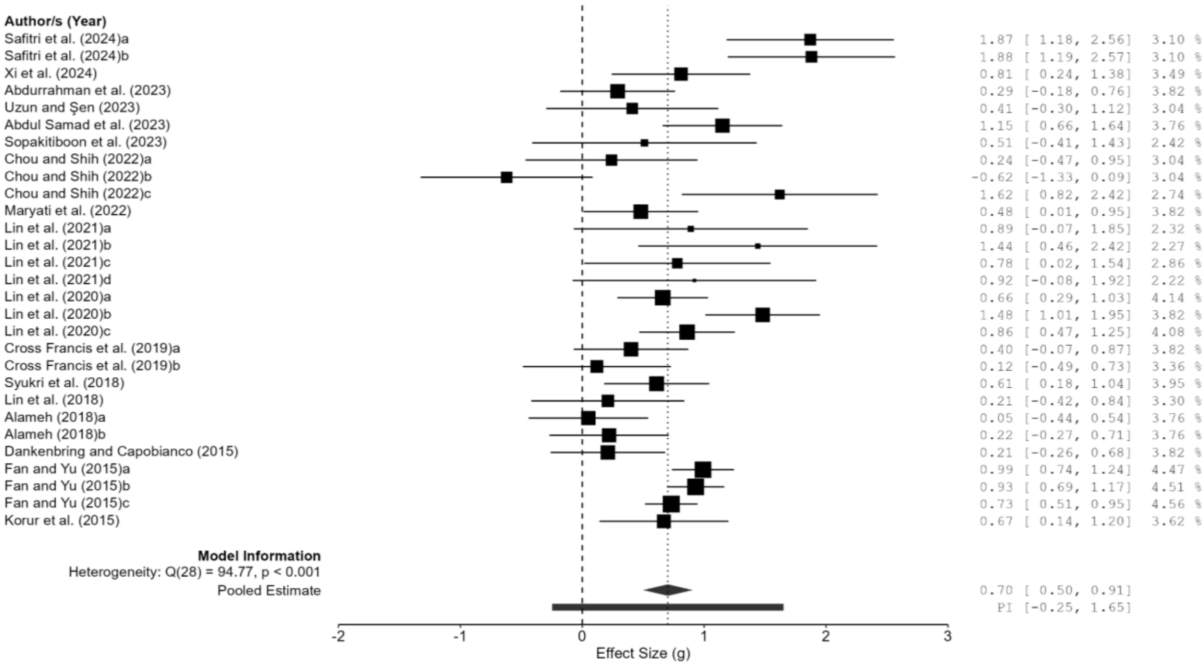

Figure 4. Forest Plot of the Effects of the EDP on Cognitive Learning Performance

Additionally, the forest plot reveals variability among the individual studies. Some variables related to cognitive learning outcomes show statistically significant positive effects, as indicated by confidence intervals (CIs) that do not cross the line of no effect (zero), while others do cross this line. Specifically, out of 29 valid datasets, 16 demonstrated that the engineering design process had a significant effect on students' cognitive learning outcomes. Furthermore, to determine the extent of variability in effect sizes across the included studies, the *Q*-statistic provides a test of the null hypothesis that all studies in the meta-analysis share a common effect size. If this were true, the expected *Q*-value would be equal to the degrees of freedom (the number of studies minus one). In this investigation, the *Q*-value is 94.765 with 28 degrees of freedom and $p < .001$, leading to the rejection of the null hypothesis, indicating that the true effect sizes differ across studies. Additionally, the I^2 statistic is 79.838%, suggesting that 79.838% of the variance in observed effects is due to true effect size differences rather than sampling error. Further, the variance of true effects ($τ^2$) is 0.224, and the standard deviation of true effects ($τ$) is 0.473. The forest plot also provides the prediction interval (PI) ranges from -0.25 to 1.65 denoted by the thick and black line below the diamond, indicating that in some 95% of populations comparable to the analysis, the true effect size will fall within this range. This suggests that while the engineering design process (EDP) may have a substantial impact on some populations, there will be others where its effect is minimal or even absent.

Furthermore, the tests above show heterogeneity but do not indicate which study influenced it, and to ensure the robustness of the meta-analytical findings sensitivity analysis was performed. Firstly, to identify potential outliers, casewise diagnostics and the Baujat plot were used to detect studies that excessively contribute to heterogeneity and overall results (Baujat et al., 2002). In Figure 5, each dot represents an individual study, with studies located in the top right quadrant exerting a stronger influence on the overall results and contributing to the most heterogeneity in the analysis. Notably, based on the analysis no influential case or dataset was found.

The study also employed the one-study-removal method to assess the robustness of the current investigation, ensuring that the results are not dependent on any single study. The findings demonstrate that the overall effect size remained within a reasonable range (0.664 - 0.740), supporting the robustness of the meta-analysis. This range also indicates that the effect size consistently fell between moderate (0.5) and large (0.8) thresholds. Meanwhile, the study weights (%) were also provided in the last column of data in the forest plot signifying that each dataset has contributed to the pooled effect size. Specifically, studies with narrower confidence intervals (less uncertainty around their effect estimate) have more weight. This is essential in ensuring that the meta-analysis gives a more accurate and representative estimate of the true effect by giving more emphasis to the most reliable studies.

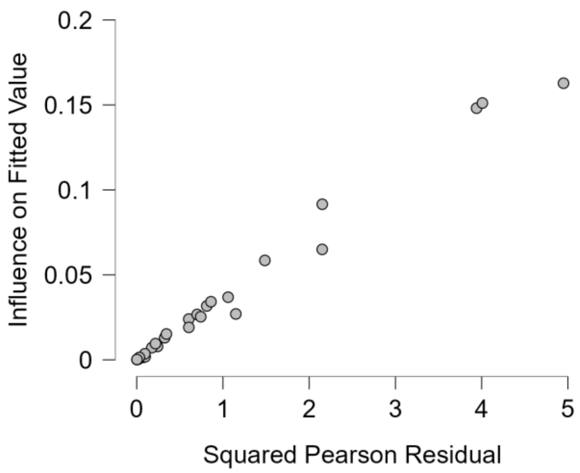

Figure 5. Identification of Datasets Contributing to Heterogeneity using the Baujat Plot

Another analysis was conducted to assess the potential for publication bias. According to Rothstein et al. (2006), publication bias refers to the tendency for studies with significant results to be published more often than those with insignificant or inconclusive findings, making published studies unrepresentative of all conducted research. Publication bias can be examined in several ways, first is by checking the funnel plot, which illustrates the distribution of effect sizes. Figure 6 (A) suggests potential asymmetry in the plot, which may indicate publication bias. However, Simmonds (2015) argues that relying solely on the visual inspection of a funnel plot can lead to a misleading conclusion about the presence or absence of publication bias. Thus, formal statistical tests for bias are generally preferred to test the asymmetry of the plot (Table 3).

Following the dotted lines in Figure 6, the funnel prediction interval is aligned with confidence levels of 0.90, 0.95, and 0.99. Meanwhile, Figure 6 (B) displays the power-enhanced funnel plot, a novel graphical display according to Kossmeier et al. (2020), used to assess the study-level power in meta-analysis. Additionally, the plot highlights the statistical power of studies to detect the true underlying effect of the engineering design process, offering a more detailed view compared to the traditional funnel plot. It includes color-coded power regions and a second power axis used for further analysis. It can be noted that the top funnel (green area) are the studies with small standard errors and have high power, these studies are more precise estimates of the effect size. Conversely, the bottom funnel (red area) is the study with large standard errors that have low power. These are typically smaller studies with less precise estimates of the effect size. Notably, based on the plot most of the studies are in a considerably high-power region suggesting that this meta-analysis, as a whole, likely has reasonable power to detect an overall effect. However, the presence of some studies in the red (low power) region highlights the potential influence of small, underpowered studies. Therefore, these studies, due to their imprecision can contribute to heterogeneity.

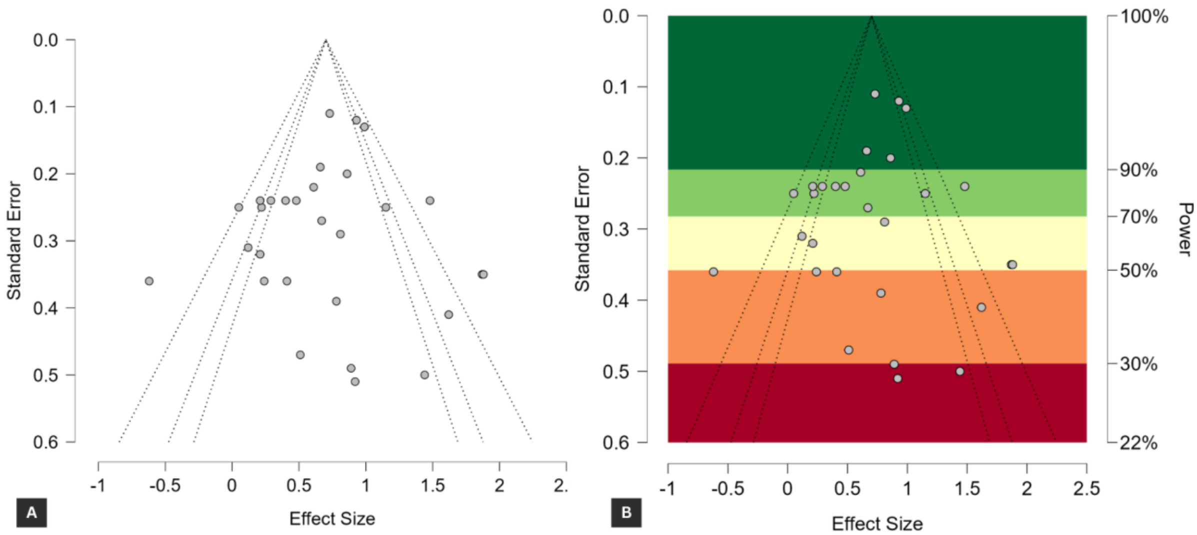

Figure 6. Conventional Funnel Plot (A) and Power-enhanced Funnel Plot (B)

Table 3 presents the results of several statistical tests for funnel plot asymmetry, which are used to assess potential publication bias in meta-analysis.

Table 3. Statistical Tests for Funnel Plot Asymmetry

Funnel Plot Asymmetry Test	**Statistic**	**value**	***p***	**95% CI (Lower)**	**95% CI (Upper)**
Fail-Safe N		2384.000	<.001		
Rank Correlation Test	τ	0.038	0.777		
Meta-Regression Test	z	1.468	0.640	0.009	1.141
Weighted Regression Test	t	-0.575	0.570	0.433	1.239
Trim-and-Fill Analysis		0.000			

The Classic Fail-Safe N test determines the number of studies with null results needed to overturn the observed effect (Rosenthal, 1979). The large Fail-Safe N value of 2384 indicates that the overall effect is robust against potential publication bias. Further, this data suggests that the current meta-analysis would need 2384 studies with an effect size of zero to nullify the observed effect. Additionally, the *p*-value of < .001 further implies that the investigation is not susceptible to publication bias. Despite these results, Borenstein (2019) argued that using Fail-Safe *N* should be avoided due to some limitations. Moreover, this method was originally designed to ensure that results were not solely due to publication bias. However, it was developed during a time when meta-analysis primarily aimed to test a specific null hypothesis. Additionally, in the modern context, where the focus is on estimating the mean effect size and testing a different null hypothesis, Fail-Safe *N* holds little relevance. Thus, other analyses can be employed to provide more insights into the data.

Additionally, the Rank Correlation Test (Kendall's tau) examines the correlation between effect sizes and their standard errors. The non-significant tau value of 0.038 ($p = 0.777$) indicates no significant association, suggesting a lack of publication bias. Similarly, the meta-regression test or Egger's test, which assesses the relationship between intervention effect size estimates on their standard errors weighted by the inverse variance, shows a non-significant *z*-value of 1.468 ($p = 0.640$), reinforcing that no significant asymmetry was detected. The weighted regression test also yields a non-significant result ($t = -0.575$, $p = 0.570$). The above statistical investigations from the funnel plot asymmetry test, supported by a *p*-value greater than 0.05, suggest that the effect size distribution is likely symmetrical. Furthermore, the Trim-and-Fill Analysis, a method that imputes potentially missing studies to correct for funnel plot asymmetry was employed, in this investigation the side where the studies to be imputed was set to the right side, and found only two (2) additional studies to be imputed (see Figure 7).

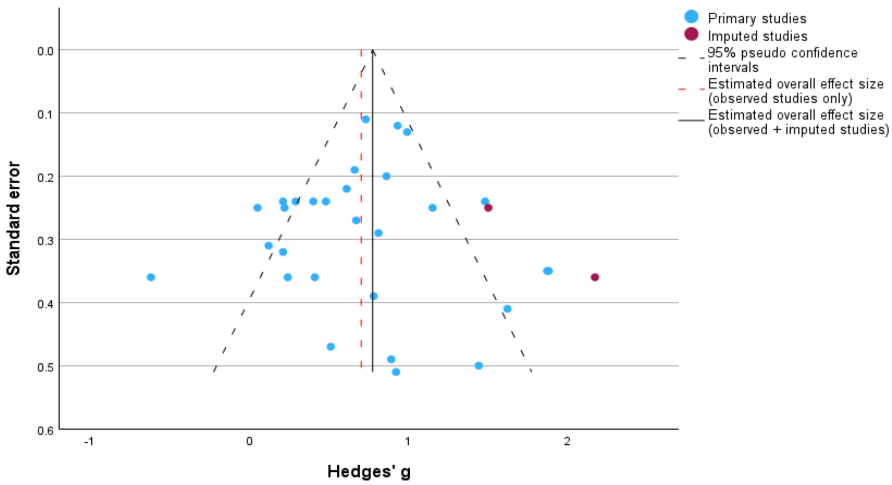

Figure 7. Funnel Plot showing the Imputed Studies in the Trim-and-Fill Analysis

Moreover, the Trim-and-Fill analysis adjusted the effect size estimate, shifting Hedges' *g* from the observed value $g = 0.70$, $p < .001$, CI [0.449, 0.905], represented by the red dashed line, to an adjusted estimate $g = 0.77$, $p < .001$, CI [0.566, 0.981], indicated by the solid black vertical line. Noteworthy, according to Mavridis and Salanti (2014), this method served as sensitivity analysis and this current investigation found that the effect sizes are still in considerable range. In summary, all of the above statistics suggest a low risk of publication bias in the current meta-analysis, corroborating the findings from the appraisal assessments for each study in different risks of bias domains provided in the methodology.

Subgroup Analysis of the Effects of the Engineering Design Process across Different Moderators

Despite the empirical evidence for the overall effectiveness of the engineering design process, the considerable heterogeneity in this meta-analysis highlights the importance of reviewing contextual factors and exploring potential moderators that may influence its effects. Additionally, Quintana (2015) described that moderating variables contribute to some of the observed variance. To examine the influence of various moderators on effect sizes and address observed heterogeneity, subgroup analyses were conducted. These inquiries examined how the engineering design process (EDP) effect size varied across different population and intervention characteristics, including geographic region, study duration, class size, group selection method, grade level, EDP model employed, and EDP skills. Moderator analysis involves partitioning the pooled data into distinct subgroups to facilitate comparisons and identify potential moderators of the overall effect (Higgins & Thomas, 2019).

Table 4 summarizes the results of the subgroup analysis of potential moderating variables identified in the study. The results revealed statistically significant variations in effect sizes across different regions ($Q = 12.052$, $df = 3$, $p = 0.007$). Significant large effect sizes were demonstrated for East Asia ($g = 0.792$, $p < 0.001$) and Southeast Asia ($g = 0.950$, $p < 0.001$). Meanwhile, West Asia showed a smaller, but statistically significant effect ($g = 0.312$, $p = 0.023$). In contrast, the Midwest USA presented a non-significant effect size ($g = 0.262$, $p = 0.078$). This may be due to differences in cultural and educational systems across regions, as well as other factors such as learning styles and student engagement. Gündüz and Özcan (2010) also argued that each student learns differently, which is why teachers must explore various teaching styles. Furthermore, it can be noted that studies conducted in the Midwest USA region had a low sample size ($k = 3$), indicating an uneven distribution of studies in the subgroup, which may result in low statistical power. Hence, the interpretation of these results should be treated with caution. Despite this, Asian students showed considerable improvement in cognitive learning outcomes after the implementation of the engineering design process.

On the other hand, subgroup analysis showed no significant differences in the duration ($Q = 2.067$, $df = 3$, $p = 0.559$). Studies lasting <3 weeks had a large effect size ($g = 0.913$, $p = 0.017$), 4-6 weeks had a medium effect size ($g = 0.533$, $p < 0.001$), and >10 weeks had an upper medium effect size ($g = 0.735$, $p = 0.017$). Conversely, studies with a 7-9 week implementation period showed a medium effect size but not significant ($g = 0.598$, $p = 0.228$). These results indicate that the length of implementation of EDP has no moderating effects. Since the engineering design process was the intervention used in the studies, it may have been the first time participants encountered this approach. Thus, the shorter implementation period with a larger effect size, such as less than 3 weeks, may have resulted in a novelty effect. According to Schomaker and Meeter (2015), a novel stimulus triggers a cascade of brain responses, activating various neuromodulatory systems. Consequently, novelty affected cognition, including improving perception and action, increasing motivation, eliciting exploratory behavior, and promoting learning. Interestingly, the 4-6 weeks and >10 weeks results have provided a significant upper-medium effect with (k=10) studies in each. It can also be inferred that the longer duration may result in better outcomes.

Meanwhile, the insignificant effect observed in the 7–9 weeks category with a medium effect size may be due to the less power of the studies and uneven distribution of datasets in the subgroup analysis. Therefore, due to these limitations, interpretations may not be conclusive.

Table 4. Subgroup Analysis according to the Identified Moderators

Moderators	**Effect Size Estimates for Subgroup Analysis**						**Subgroup Homogeneity**		
	k	***g***	***Lower***	***Upper***	***z***	***p***	***Q***	***df***	***p***
Geographic Region							12.052	3	**0.007***
East Asia	15	0.792	0.521	1.063	5.718	**<.001**			
South East Asia	7	0.950	0.456	1.445	3.766	**<.001**			
West Asia	4	0.312	0.044	0.580	2.281	**0.023**			
Midwest USA	3	0.262	-0.029	0.554	1.762	0.078			
Duration							2.067	3	0.559
<3 weeks	5	0.913	0.166	1.661	2.395	**0.017**			
4-6 weeks	10	0.533	0.320	0.746	4.907	**<.001**			
7-9 weeks	4	0.598	-0.375	1.571	1.205	0.228			
>10 weeks	10	0.735	0.166	1.661	2.395	**0.017**			
Class Size							3.168	3	0.366
1-30	10	0.591	0.194	0.989	2.918	**0.004**			
31-50	13	0.648	0.316	0.981	3.820	**<.001**			
51-100	3	0.983	0.499	1.466	3.986	**<.001**			
>100	3	0.872	0.719	1.025	11.156	**<.001**			
Group Selection							5.929	1	**0.015***
Randomized	16	0.917	0.683	1.150	7.699	**<.001**			
Nonrandomized	13	0.453	0.194	0.163	0.744	**0.002**			
Grade Level							10.371	4	**0.035***
preschool	3	0.983	0.499	1.466	3.986	**<.001**			
elementary	4	0.346	-0.563	1.255	0.746	0.456			
middle school	4	0.312	-0.199	0.860	2.281	**0.023**			
high school	13	0.790	0.484	1.097	5.057	**<.001**			

Moderators	Effect Size Estimates for Subgroup Analysis						Subgroup Homogeneity		
	k	*g*	*Lower*	*Upper*	*z*	*p*	*Q*	*df*	*p*
university level	5	0.884	0.477	1.292	4.251	**<.001**			
EDP Model							10.847	3	**0.013***
AIPCTI	7	0.811	0.522	1.099	5.509	**<.001**			
DDCTPE	17	0.775	0.534	1.015	6.319	**<.001**			
EDIPT	2	0.135	-0.211	0.481	0.764	0.455			
CTC	3	0.401	-0.877	1.680	0.615	0.538			
EDP Skills							11.149	1	**<.001***
Core Engineering Knowledge and Practice	17	0.451	0.272	0.631	4.933	**<.001**			
Cognition and Thinking	12	1.047	0.747	1.349	6.833	**<.001**			

*Random-effects model: *Moderating effect, p<.05*

Furthermore, the non-significant *Q* value for subgroup homogeneity (*Q = 3.168*, *df = 3*, *p = 0.366*) indicates that class size had no moderating effects. However, individual class size categories showed varying results. Smaller classes (1-30 students) demonstrated a statistically significant upper-medium effect ($g = 0.591$, $p = 0.004$), as did classes with 31-50 students ($g = 0.648$, $p<.001$). Meanwhile, classes with 51-100 students and over 100 students yielded large effect sizes ($g = 0.983$, $p < .001$) and ($g = 0.872$, $p < .001$), respectively. Furthermore, all individual class size categories showed statistically significant effects, the overall test for subgroup homogeneity suggests that class size, when considered as a whole, does not have a moderating effect. Based on these findings, it appears that large class sizes such as 51-100 and over 100 students exhibit the largest effect, suggesting that multiple teachers may be required to manage such large groups during EDP implementation similar to studies of Fan and Yu (2015) and Lin et al. (2020). Despite these results, the interpretations are not conclusive due to the uneven distribution of studies in the subgroup. Specifically, the class size with a large effect size is only represented by three studies (k=3). Interestingly, small class sizes such as 1-30 ($k = 10$) and 31-50 ($k = 13$) had a significant upper-medium effect size in enhancing cognitive learning performance through the implementation of the engineering design process and this is supported by most of the studies included in the meta-analysis.

On the other hand, the subgroup homogeneity test ($Q = 5.929$, $df = 1$, $p = 0.015$) indicates that the effect sizes differ significantly between group selection methods (randomized vs. nonrandomized), suggesting that group selection acts as a moderator. Randomized selection showed a larger, significant effect ($g = 0.917$, $p < .001$,) compared to non-randomized selection ($g = 0.453$, $p = 0.002$). This analysis suggests that studies employing random assignment of participants to treatment and control groups demonstrated a stronger effect of the engineering design process on cognitive learning outcomes. While studies that did not use randomization found a less effect. According to Pierre (2001), randomly assigning units to treatment and control groups provides researchers with the most robust basis for drawing causal inferences between the intervention and the observed outcomes. Conversely, non-randomized studies are more susceptible to bias, which could either inflate or deflate the observed effect size. Overall, this analysis provides substantial evidence that the selection of participants into groups has a moderating effect.

A significant difference was also found across grade levels (Q = 10.371, df = 4, p = 0.035), this indicates that grade level has a moderating effect. Large positive effects were observed in preschool (g = 0.983, p < .001), high school (g = 0.790, p < .001), and university level (g = 0.884, p < .001). Meanwhile, a small, but still significant, positive effect was observed in middle school (g = 0.312, p = 0.023). On the other hand, the elementary level did not show a significant effect (g = 0.346, p = 0.456). Findings suggest that the effect of the engineering design process varies across different educational stages, with greater potential in preschool and university levels exhibiting the largest effects. These results also corroborate the distribution of studies that implemented engineering design processes across different educational stages, as reported by Winarno et al. (2020). They also emphasized the implementation gaps of the EDP at the undergraduate and graduate levels compared to other educational stages. Due to the uneven distribution of studies in the subgroup analysis, the interpretations should be treated judiciously. Despite these results, the engineering design process positively impacts cognitive learning performance across educational levels, with large effects among high school students (g = 0.790, p < .001) supported by 13 datasets.

Additionally, a significant difference was found across EDP models (Q = 10.847, df = 3, p = 0.013), indicating the EDP model as a moderator and this variable could also cause heterogeneity. Large positive effects were observed for AIPCTI (g = 0.811, p < .001) and DDCTPE (g = 0.775, p < .001). While, EDIPT (g = 0.135, p = 0.455) and CTC (g = 0.401, p = 0.538) did not show significant effects. These findings suggest that the chosen EDP model influences the observed effect size, with AIPCTI and DDCTPE demonstrating stronger effects compared to the other models. Furthermore, according to the Texas Education Agency (n.d.), the design process is iterative, meaning some stages may need to be repeated before progressing. The design might require modifications and improvements until it meets the specified criteria. Although there are predefined steps, the process is not linear or sequential. Notably, it is important to note that while these EDP models have comparable stages, there are differences and distinct features between them. Therefore, understanding the stages of the EDP is essential for performing the problem-solving process effectively. Due to the uneven distribution and insufficient number of studies in other EDP models, such as EDIPT (k=2) and CTC (k=3), the interpretations may not be conclusive. However, this research suggests that the DDCTPE and AIPCTI models can be adopted for the implementation of the engineering design process.

Furthermore, a significant difference was observed between skill categories (Q = 11.149, df = 1, p < .001), suggesting that EDP skills had a moderating effect. Significant positive effects were found for both Core Engineering Knowledge and Practice (g = 0.451, p < .001) and Cognition and Thinking (g = 1.047, p < .001). These broad skills are derived from the four dimensions of engineering skills according to Abdulwahed and Hasna (2016), two of which are Professional and Interpersonal and Business and Management. However, only the first two dimensions were considered in this context. *Core Engineering Knowledge and Practice* encompasses Math, Physics, and Science Fundamentals (MPSF), Disciplinary Knowledge (Depth), Interdisciplinary Knowledge (Breadth), Multidisciplinary Knowledge (MDK), Practical Skills (PrS), and Information and Computer Technology Skills (ICTS). Meanwhile, *Cognition and Thinking* include Problem-Solving Skills (PSS), Lifelong Learning (LLL), Decision-Making Skills (DMS), Systems Thinking Approach (STA), Critical Thinking (ClT), Innovation Skills (InS), and System Design Skills (SDS). In this current meta-analysis, results show that the implementation of the engineering design process (EDP) has more effects on the cognitive learning performances related to Cognition and Thinking compared to Core Engineering Knowledge and Practice. This result is supported by the argument of Yu et al. (2024), who stated that design thinking models consist of multiple stages, whereas some models are difficult and challenging. Consequently, their impact on self-efficacy tends to be smaller compared to other types of learning outcomes. Lastly, the current meta-analysis is corroborated by the impact of the engineering design process on problem-solving (Maryati et al., 2022), system thinking (Abdurrahman et al., 2023), and critical thinking ability (Safitri et al., 2024).

Conclusion

This meta-analysis investigated the effectiveness of the engineering design process (EDP) in improving students' cognitive learning outcomes. The study utilized 17 studies with 29 valid datasets from different geographic regions, implemented across various educational levels and subject areas. The documents included in this meta-analysis were published between 2015 and 2024, all sourced from reputable journals and universities. Meanwhile, out of the 17 studies, most are original research articles, one is a conference paper, and another is a final thesis manuscript. Each investigation focused on distinct cognitive learning variables that were enhanced through the implementation of the engineering design process (EDP). The current meta-analysis revealed that the implementation of the engineering design process has a significant effect on cognitive learning outcomes (g = 0.70, p < .001), suggesting that the intervention has an upper-medium effect. Notably, this result is corroborated by previous scholarly works on design thinking and the engineering design process. Moreover, the subgroup analysis showed that there are significant differences among the moderators namely geographic region, group selection, grade level, EDP model, and EDP skills. This suggests that to achieve a substantial effect of the engineering design process on students' cognitive learning outcomes, its implementation must consider these relevant variables.

Noteworthy, the research also provided insights that randomizing students into treatment and control groups offers the most robust basis for drawing causal inferences between the intervention and the observed outcomes. Interestingly, Asian students demonstrated significant improvement in cognitive learning outcomes following the implementation of the engineering design process. Conversely, the investigation also revealed that the duration of implementation and class size do not moderate the effects of the engineering design process. This implies that the engineering design process can be implemented in various class sizes or grade levels; however, for larger classes, the involvement of multiple and skilled teachers is recommended. Additionally, the AIPCTI *(Ask, Imagine, Plan, Create, Test, Improve)* and DDCTPE *(Define the problem, Decide possible solutions, Create the design, Test, Present, Evaluate)* were the commonly used EDP models in the meta-analysis resulting in an upper-medium to large effect on students' cognitive learning performance. Overall, the implementation of the engineering design process yields a significant medium to large effect size on core engineering knowledge and practice including the skills related to cognition and thinking.

Limitations of the Research and Recommendations for Future Practice and Work

This meta-analysis provides empirical evidence on the effects of the engineering design process on students' cognitive learning outcomes. To further guide the implementation of EDP, the following recommendations are offered for future practice and opportunities for continued scholarly work.

1. It can be inferred that Asian students have experienced the engineering design process, and the research has primarily focused on this region using control and experimental groups. However, more studies should be conducted in other regions, such as America, Australia, Europe, and Africa, to further strengthen and validate the results of this meta-analysis.
2. The duration of EDP implementation is not a significant factor based on the results. However, further studies with varying durations are needed to investigate the effects of the engineering design process (EDP) more thoroughly. Notably, using a valid dataset with (k = 10) for each duration of 4–6 weeks and over 10 weeks may produce effect sizes up to the upper-medium range on cognitive learning outcomes. This also suggests that increased exposure to EDP may lead to better learning outcomes.
3. Class size may not be a significant factor in the implementation of the engineering design process (EDP) based on the results. However, smaller class sizes, such as 1-30 and 31-50, may produce an above-medium effect size. Additionally, larger class sizes resulted in a larger effect size; however, these results are not conclusive due to the uneven distribution of studies. Nonetheless, the findings suggest that to effectively implement EDP in larger class sizes, more skilled teachers should be involved. Likewise, this research recommends that other scholars also conduct research with 51-100 and >100 participants to provide more insights on EDP.
4. Randomization is a crucial factor in research design. By randomly assigning learners to treatment and control groups, researchers establish a strong foundation for making causal inferences between the intervention and the observed outcomes. This process not only helps eliminate bias in the study but also ensures that the groups are comparable at the start of the investigation, reducing the influence of confounding variables.
5. Grade level is a key factor in the implementation of the engineering design process (EDP) across various educational levels. High school (k = 13), in particular, had a large impact. Conversely, insignificant effects were observed at the elementary level. However, this interpretation is not conclusive due to the uneven distribution of studies. Further research should be carried out at the preschool, elementary, middle school, and university levels.
6. The engineering design process (EDP) model is a crucial factor to consider in its implementation. Based on the results, the researcher recommends the following models: DDCTPE *(Define the problem, Decide possible solutions, Create the design, Test, Present, Evaluate)* and AIPCTI *(Ask, Imagine, Plan, Create, Test, Improve)*. On the other hand, further analysis should be conducted on other models.
7. Conclusively, the engineering design process enhanced the core engineering knowledge and practice

including the skills related to cognition and thinking of the students. Noteworthy, this meta-analysis is only limited to cognitive learning outcomes other variables may be explored.

8. As guidance for future researchers who will work with the same approach, it is recommended that team size be included in the methodology if the teacher divides the groups into smaller engineering design teams. This moderator was not included in the present meta-analysis due to limited reporting in most studies.

References

studies included in the meta-analysis

*Abdul Samad, N., Osman, K., & Nayan, N. A. (2023). Computational Thinking Through the Engineering Design Process in Chemistry Education. *International Journal of Educational Methodology*, *9*(4), 771–785. https://doi.org/10.12973/ijem.9.4.771

*Abdulwahed, M., & Hasna, M. O. (2016). Engineering and Technology Talent for Innovation and Knowledge-Based Economies. In *Springer eBooks*. Springer Nature. https://doi.org/10.1007/978-3-319-46439-8

*Abdurrahman, A., Maulina, H., Nurulsari, N., Sukamto, I., Umam, A. N., & Mulyana, K. M. (2023). Impacts of integrating engineering design process into STEM makerspace on renewable energy unit to foster students' system thinking skills. *Heliyon*, *9*(4), e15100. https://doi.org/10.1016/j.heliyon.2023.e15100

*Alameh, S. H. (2018). Effect of science and engineering practices in biology on students attitudes, achievement and engineering design skills - [Thesis]. In *Handle.net* (pp. 1–232). https://doi.org/b21091699

Barker, T. H., Habibi, N., Aromataris, E., Stone, J. C., Leonardi-Bee, J., Sears, K., Sabira Hasanoff, Miloslav Klugar, Catalin Tufanaru, Sandeep Moola, & Munn, Z. (2024). The Revised JBI Critical Appraisal Tool for the Assessment of Risk of Bias for Quasi-Experimental Studies. *JBI Evidence Synthesis*, *22*(3), 378–388. https://doi.org/10.11124/jbies-23-00268

Baujat, B., Mahé, C., Pignon, J.-P., & Hill, C. (2002). A graphical method for exploring heterogeneity in meta-analyses: application to a meta-analysis of 65 trials. *Statistics in Medicine*, *21*(18), 2641–2652. https://doi.org/10.1002/sim.1221

Borenstein, M. (2019). *Common Mistakes in Meta-Analysis*. Biostat, Inc.

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2009). Introduction to Meta-Analysis. In *Introduction to Meta-Analysis*. John Wiley & Sons. https://doi.org/10.1002/9780470743386

Bunprom, S., Tupsai, J., & Yuenyong, C. (2019). Learning Activities to Promote the Concept of Engineering Design Process for Grade 10 Students' Ideas about Force and Motion through Predict-Observe-Explain (POE). *Journal of Physics: Conference Series*, *1340*(1), 1–9. https://doi.org/10.1088/1742-6596/1340/1/012081

Capobianco, B. M., Yu, J. H., & French, B. F. (2014). Effects of Engineering Design-Based Science on Elementary School Science Students' Engineering Identity Development across Gender and Grade. *Research in Science Education*, *45*(2), 275–292. https://doi.org/10.1007/s11165-014-9422-1

Chalmers, I., & Altman, D. G. (1995). *Systematic reviews*. BMJ Publishing Group.

*Chou, P.-N., & Shih, R.-C. (2022). Engineering Design Thinking in LEGO Robot Projects: An Experimental

Study. In: Huang, YM., Cheng, SC., Barroso, J., Sandnes, F.E. (eds) Innovative Technologies and Learning. *ICITL 2022. Lecture Notes in Computer Science*, *13449*, 324–333. https://doi.org/10.1007/978-3-031-15273-3_36

Çikrıkci, Ö. (2016). The effect of internet use on well-being: Meta-analysis. *Computers in Human Behavior*, *65*, 560–566. https://doi.org/10.1016/j.chb.2016.09.021

*Cross Francis, D., Tan, V., & Nicholas, C. (2019). Supporting disciplinary and interdisciplinary knowledge development and design thinking in an informal, pre-engineering program: A Workplace Simulation Project. *School Science and Mathematics*, *119*(7), 382–395. https://doi.org/10.1111/ssm.12364

*Dankenbring, C., & Capobianco, B. M. (2015). Examining Elementary School Students' Mental Models of Sun-Earth Relationships as a Result of Engaging in Engineering Design. *International Journal of Science and Mathematics Education*, *14*(5), 825–845. https://doi.org/10.1007/s10763-015-9626-5

De Cassai, A., Boscolo, A., Zarantonello, F., Pettenuzzo, T., Sella, N., Geraldini, F., Munari, M., & Navalesi, P. (2023). Enhancing study quality assessment: an in-depth review of risk of bias tools for meta-analysis—a comprehensive guide for anesthesiologists. *Journal of Anesthesia, Analgesia and Critical Care*, *3*(1). https://doi.org/10.1186/s44158-023-00129-z

*Fan, S.-C., & Yu, K.-C. (2015). How an integrative STEM curriculum can benefit students in engineering design practices. *International Journal of Technology and Design Education*, *27*(1), 107–129. https://doi.org/10.1007/s10798-015-9328-x

Fidai, A., Barroso, L. R., Capraro, M. M., & Capraro, R. M. (2020). Effects of Engineering Design Process on Science and Mathematics. *2021 IEEE Frontiers in Education Conference (FIE)*, 1–4. https://doi.org/10.1109/fie44824.2020.9274167

Goktepe Yildiz, S., & Ozdemir, A. S. (2018). The effects of engineering design processes on spatial abilities of middle school students. *International Journal of Technology and Design Education*, *30*(1), 127–148. https://doi.org/10.1007/s10798-018-9491-y

Gündüz, N., & Özcan, D. (2010). Learning styles of students from different cultures and studying in Near East University. *Procedia - Social and Behavioral Sciences*, *9*, 5–10. https://doi.org/10.1016/j.sbspro.2010.12.107

Hafiz, N. R. M., & Ayop, S. K. (2019). Engineering Design Process in Stem Education: A Systematic Review. *International Journal of Academic Research in Business and Social Sciences*, *9*(5), 676–697. https://doi.org/10.6007/IJARBSS/v9-i5/5998

Hansen, C., Steinmetz, H., & Block, J. (2021). How to conduct a meta-analysis in eight steps: a practical guide. *Management Review Quarterly*, *72*(1). https://doi.org/10.1007/s11301-021-00247-4

Higgins, J., & Thomas, J. (2019). *Cochrane Handbook For Systematic Reviews Of Interventions.* (2nd ed.). Wiley-Blackwell. https://training.cochrane.org/handbook/current

*Korur, F., Efe, G., Erdogan, F., & Tunç, B. (2015). Effects of Toy Crane Design-Based Learning on Simple Machines. *International Journal of Science and Mathematics Education*, *15*(2), 251–271. https://doi.org/10.1007/s10763-015-9688-4

Kossmeier, M., Tran, U. S., & Voracek, M. (2020). Power-Enhanced Funnel Plots for Meta-Analysis. *Zeitschrift Für Psychologie*, *228*(1), 43–49. https://doi.org/10.1027/2151-2604/a000392

LaKose, C. (2015). *The inclusion of engineering design into the high school biology The inclusion of engineering* *design into the high school biology curriculum* (pp. 1–63) [Graduate Research Papers. 75]. https://scholarworks.uni.edu/grp/75/

*Lin, K.-Y., Hsiao, H.-S., Chang, Y.-S., Chien, Y.-H., & Wu, Y.-T. (2018). The Effectiveness of Using 3D Printing Technology in STEM Project-Based Learning Activities. *EURASIA Journal of Mathematics, Science and Technology Education*, *14*(12). https://doi.org/10.29333/ejmste/97189

*Lin, K.-Y., Wu, Y.-T., Hsu, Y.-T., & Williams, P. J. (2021). Effects of infusing the engineering design process into STEM project-based learning to develop preservice technology teachers' engineering design thinking. *International Journal of STEM Education*, *8*(1). https://doi.org/10.1186/s40594-020-00258-9

*Lin, X., Yang, W., Wu, L., Zhu, L., Wu, D., & Li, H. (2020). Using an inquiry-based science and engineering program to promote science knowledge, problem-solving skills and approaches to learning in preschool children. *Early Education and Development*, *32*(5), 1–19. https://doi.org/10.1080/10409289.2020.1795333

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis*. Sage Publications.

*Maryati, R. E., Permanasari, A., & Ardianto, D. (2022). Fluid Learning with Arduino-Based on Engineering Design Process (EDP) to Improve Student's Problem Solving Ability. *Scientiae Educatia: Jurnal Pendidikan Sains*, *11*(2). https://doi.org/10.24235/sc.educatia.v11i2.11760

Mavridis, D., & Salanti, G. (2014). How to assess publication bias: funnel plot, trim-and-fill method and selection models. *Evidence Based Mental Health*, *17*(1), 30–30. https://doi.org/10.1136/eb-2013-101699

McGuinness, L. A., & Higgins, J. P. T. (2020). Risk-of-bias VISualization (robvis): An R package and Shiny web app for visualizing risk-of-bias assessments. *Research Synthesis Methods*, *12*(1). https://doi.org/10.1002/jrsm.1411

Panergayo, A. A. E., & Prudente, M. S. (2024). Effectiveness of Design-based Learning in Enhancing Scientific Creativity in STEM Education: A Meta-analysis. *International Journal of Education in Mathematics, Science and Technology*, *12*(5), 1182–1196. https://doi.org/10.46328/ijemst.4306

Pierre, R. G. St. (2001). Random Assignment: Implementation in Complex Field Settings. *Elsevier EBooks*, 12731–12734. https://doi.org/10.1016/b0-08-043076-7/00735-x

Quintana, D. S. (2015). From pre-registration to publication: a non-technical primer for conducting a meta-analysis to synthesize correlational data. *Frontiers in Psychology*, *6*(Article 1549). https://doi.org/10.3389/fpsyg.2015.01549

Radloff, J. D., Guzey, S., Eichinger, D., & Capobianco, B. M. (2019). Integrating Engineering Design in Undergraduate Biology Using a Life Science Design Task. *Journal of College Science Teaching*, *49*(2), 45–52. https://www.jstor.org/stable/26901367

Riffenburgh, R. H. (2012). Sample Size Estimation and Meta-Analysis. In *Elsevier eBooks* (pp. 365–391). Elsevier BV. https://doi.org/10.1016/b978-0-12-384864-2.00018-4

Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, *86*(3), 638–641. https://doi.org/10.1037/0033-2909.86.3.638

Rothstein, H. R., Sutton, A. J., & Borenstein, M. (2006). *Publication Bias in Meta-Analysis Prevention, Assessment and Adjustments*. John Wiley & Sons.

*Safitri, W., Suyanto, S., & Prasetya, W. A. (2024). The Influence of the STEM-Based Engineering Design Process Model on High School Students' Creative and Critical Thinking Abilities. *Jurnal Penelitian*

Pendidikan IPA, *10*(2), 662–673. https://doi.org/10.29303/jppipa.v10i2.4765

Sawilowsky, S. (2009). New Effect Size Rules of Thumb. *Journal of Modern Applied Statistical Methods*, *8*(2). https://doi.org/10.22237/jmasm/1257035100

Schomaker, J., & Meeter, M. (2015). Short- and long-lasting consequences of novelty, deviance and surprise on brain and cognition. *Neuroscience & Biobehavioral Reviews*, *55*, 268–279. https://doi.org/10.1016/j.neubiorev.2015.05.002

Selcen Guzey, S., Harwell, M., Moreno, M., Peralta, Y., & Moore, T. J. (2016). The Impact of Design-Based STEM Integration Curricula on Student Achievement in Engineering, Science, and Mathematics. *Journal of Science Education and Technology*, *26*(2), 207–222. https://doi.org/10.1007/s10956-016-9673-x

Simmonds, M. (2015). Quantifying the risk of error when interpreting funnel plots. *Systematic Reviews*, *4*(1). https://doi.org/10.1186/s13643-015-0004-8

*Sopakitiboon, T., Tuampoemsab, S., Howimanporn, S., & Chookaew, S. (2023). Implementation of New-Product Creativity through an Engineering Design Process to Foster Engineering Students' Higher-Order Thinking Skills. *International Journal of Engineering Pedagogy (IJEP)*, *13*(5), 4–15. https://doi.org/10.3991/ijep.v13i5.38863

Sudrajat, U., Ardianto, D., & Permanasari, A. (2023). Engineering Design Process (EDP)-Based Learning to Enhance High School Students' Creativity in Alternative Energy Topics. *Jurnal Penelitian Pendidikan IPA*, *9*(11), 9547–9553. https://doi.org/10.29303/jppipa.v9i11.5248

*Syukri, M., Halim, L., Mohtar, L. E., & Soewarno, S. (2018). The Impact of Engineering Design Process in Teaching and Learning to Enhance Students' Science Problem-Solving Skills. *Jurnal Pendidikan IPA Indonesia*, *7*(1), 66–75. https://doi.org/10.15294/jpii.v7i1.12297

TeachEngineering. (2023). What is Engineering? - TeachEngineering. *www.teachengineering.org*. https://www.teachengineering.org/k12engineering/what

Texas Education Agency. (n.d.). Engineering Design Process (EDP). In *Texas Education Agency*. https://tea.texas.gov/academics/221013-teabriefs-enginerring-design-process.pdf

Tipmontiane, K., & Williams, P. J. (2021). The Integration of the Engineering Design Process in Biology-related STEM Activity: A Review of Thai Secondary Education. *ASEAN Journal of Science and Engineering Education*, 2(1), 1–10. https://doi.org/10.17509/ajsee.v2i1.35097

Turner, H. M., III, & Bernard, R. M. (2006). Calculating and Synthesizing Effect Sizes. *Contemporary Issues in Communication Science and Disorders*, *33*(Spring), 42–55. https://doi.org/10.1044/cicsd_33_s_42

*Uzun, S., & Şen, N. (2023). The effects of a STEM-based intervention on middle school students science achievement and learning motivation. *Journal of Pedagogical Research*, *7*(1). https://doi.org/10.33902/jpr.202319315

Wilson, D. B. (2023). *Practical meta-analysis effect size calculator (Version 2023.11.27).* https://www.campbellcollaboration.org/calculator/

Winarno, N., Rusdiana, D., Samsudin, A., Susilowati, E., Ahmad, N. J., & Afifah, R. M. A. (2020). Synthesizing Results from Empirical Research on Engineering Design Process in Science Education: A Systematic Literature Review. *Eurasia Journal of Mathematics, Science and Technology Education*, *16*(12), em1912. https://doi.org/10.29333/ejmste/9129

Xi, F., Ma, H., Pi, Z., Dong, Y., Sun, J., & Jin, R. (2024). Integrating the engineering design process into the conceive-design-implement-operate model for promoting high school students' STEM competence. *Educational Technology Research and Development*, *72*(4), 2267–2295. https://doi.org/10.1007/s11423-024-10377-7

Yoon, S. H. (2023). Effects of Design Thinking Interventions on Educational Outcomes: A Meta-Analysis. *Canadian Journal of Educational and Social Studies*, *3*(1). https://doi.org/10.53103/cjess.v3i1.108

Yu, Q., Yu, K., & Lin, R. (2024). A meta-analysis of the effects of design thinking on student learning. *Humanities and Social Sciences Communications*, *11*(1). https://doi.org/10.1057/s41599-024-03237-5

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