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The Effect of Size of Deep Learning Models in Science Learning

Tomi Apra Santosa
Akademi Teknik Adikarya Kerinci, Jambi, Indonesia, 37161
Corresponding email: santosa2021@yahoo.com

Abstract

The study found out the influence of the deep learning model in science learning. This research is a type of quantitative research with a meta-analysis approach. The source of research data is 12 national journals indexed by SINTA, DOAJ or EBSCO. The eligibility criteria are that the research must be a quantitative method, the experimental method, the journal is published in 2022-2025, the research must be relevant, the participants come from elementary, junior high, high school and college students. Data analysis is quantitative analysis with the help of JASP applications. The results of this study can be concluded that there is a significant influence of the deep learning model in science learning with an effect size value of 0.915 in the high effect size category. These findings explain that the deep learning model is effectively applied at the elementary school to university education levels.

Keywords: *Deep Learning Model; Meta-analysis; Effect Size; Science Learning*

1. Introduction

Natural Science (IPA) learning has a strategic role in shaping students' scientific literacy as an important foundation in facing the challenges of the 21st century (Winiasri et al., 2023; Zulkifli et al., 2022; Zulyusri et al., 2023). Scientific literacy includes not only understanding scientific concepts, but also the ability to think critically, solve problems, and make decisions based on scientific evidence. According to Bybee (2010), scientific literacy allows individuals to be actively involved in social, economic, and environmental issues related to science, as well as understand the impact of science in daily life(Elfira & Santosa, 2023; Nurtamam et al., 2023; Ichsan et al., 2023; Markiano Solissa et al., 2023; Uluk et al., 2024). Therefore, meaningful science learning is indispensable to develop students who not only know scientific facts, but are also able to apply them reflexively and responsibly in real-life contexts (Luciana, 2022; Oktarina et al., 2021; Asnur et al., 2024)

In addition, increasing scientific literacy through science learning is important in forming citizens who think rationally and evidence-based. In the context of education, scientific literacy is one of the important indicators in assessing the quality of education in a country (Abdullah et al., 2024; Youna Chatrine Bachtiar et al., 2023; Yulianti, 2020). The OECD (2019) in the Program for International Student Assessment (PISA) emphasizes that scientific literacy is the ability to explain phenomena scientifically, evaluate and design scientific investigations, and interpret data and evidence critically (Santosa et al., 2025; Ali et al., 2024). Therefore, science learning in schools should be designed not only to deliver content, but also to foster the deep conceptual understanding, scientific attitudes, and high-level thinking skills necessary for intact scientific literacy (Goh et al., 2017; Chandra et al., 2023; Hohman et al., 2019).

One of the main problems in science learning is the teaching approach that is still conventional and teacher-centered, so it does not encourage active participation and conceptual understanding of students (Dewanto et al., 2023; Wantu et al., 2024; Uluk et al., 2024). Many teachers tend to deliver material through lectures and memorization of facts, rather than with a contextual approach or scientific inquiry that allows students to explore and understand concepts through hands-on experience(Grover et al., 2015; Ahmed et al., 2010). This causes low interest and motivation of students in learning science, as well as has an impact on the lack of development of critical thinking and problem-solving skills which are an important part of scientific literacy (Rahayu, 2017). In addition, limitations in the use of interactive learning media and technologies also reinforce the tendency to passive learning among students (Morgan & Jacobs, 2020).

Another crucial problem is the gap between the science material taught in schools and the reality of students' daily lives, which makes it difficult for students to understand the relevance of science in their lives(Reichstein et al., 2019; Agrawal & Choudhary, 2019). A dense but less applicable curriculum makes many students learn only to meet the demands of evaluation, not to build meaningful understanding. According to Yuliati (2014), the lack of application of problem-based and project-based learning approaches causes students to not be used to applying science concepts in a real context, even though these skills are very important to face the global challenges of the 21st century(Utomo et al., 2023; Hussain et al., 2023). The low pedagogic competence of science teachers in developing inquiry-based learning and technology also exacerbates this condition, so innovation is needed in learning strategies that are more in line with the characteristics and needs of today's students (Ichsan et al., 2023; Fitri & Asrizal, 2023; Asrizal et al., 2022).

The development of Artificial Intelligence (AI) technology has driven significant transformation in the world of education, especially through the application of deep learning that is able to mimic the way the human brain works in processing data and recognizing patterns(Eraslan et al., 2019). Deep learning, which is a branch of machine learning, has been widely used in adaptive learning systems, material recommendation systems, to real-time emotion detection and analysis of student performance. This technology provides the ability to design a more personalized, responsive, and data-driven learning experience(Shoaib et al., 2023). According to Zawacki-Richter et al. (2019), the integration of AI in education, especially through deep learning, has the potential to create a more inclusive and efficient learning system, by accommodating differences in students' learning styles and speeds (Ningsih et al., 2023; Hariyadi et al., 2023).

In addition to providing personalization support, the use *of deep learning* in learning also allows for automated content development such as question creation, automatic assessment, as well as translation and simplification of teaching materials(Blier & Ollivier, 2018). In the context of science learning, *deep learning* is used to simulate virtual experiments, microscopic image analysis, and predict laboratory results based on previous data. According to Holmes et al. (2021), *deep learning* is not only a technical tool, but also a means to develop new pedagogical approaches that are more interactive and evidence-based. With its ability to process big data and generate accurate predictive models, *deep learning* has opened up new opportunities for improving the quality and effectiveness of the learning process, especially in complex subjects such as natural sciences (Rudin & Wagstaff, 2014).

Research by Chen et al. (2020) shows that the use of Natural Language Processing(NLP)-based deep learning models in adaptive learning systems can significantly improve students' understanding of science concepts and retention. The study used the BERT model as the basis for a content recommendation system, and found that students who learned with AI-based systems showed an 18% improvement in learning outcomes compared to the control group. This shows the great potential of deep learning technology in improving science learning, especially when the model is designed to tailor the material to students' ability levels and interests (Sharma & Chaudhary, 2023); (Rajput et al., 2023; Li et al., 2024; Fintz et al., 2022).

However, the size of the deep learning model is an important issue in its application in the educational environment. A study by Zhang et al. (2022) compared the performance of the BERT-base and DistilBERT models in the classification tasks of high school-level science questions. The results showed that although BERT-base had higher accuracy, the smaller DistilBERT was able to deliver close results with much faster and more efficient processing times. This study confirms that the size of the deep learning model is not always directly proportional to its effectiveness in the context of learning, especially when considering the limitations of technological infrastructure in educational institutions. Therefore, it is important to further explore the influence of model size on the quality of science learning in order to obtain a model that balances performance, efficiency, and accessibility.

2. Research Methods

This study is a quantitative study with a meta-analysis approach that aims to examine the influence of the size of the deep learning model in science learning. Meta-analysis was chosen as an approach because it is able to synthesize the results of various previous studies to obtain more generalist and accurate conclusions regarding the effectiveness of an intervention (Borenstein et al., 2011; Tamur et al., 2021). The data sources for this study consist of 12 national journal articles that have been indexed by SINTA, DOAJ, or EBSCO, with inclusion criteria: (1) the research uses a quantitative approach, (2) uses experimental or quasi-experimental methods, (3) is published in the range of 2022 to 2025, (4) has direct relevance to the use of deep learning in science learning, and (5) involving participants from elementary, junior high, high school, or university levels. The data were encoded based on the characteristics of the study (year, level of education, model size, and science learning outcomes), then analyzed quantitatively using the JASP application to obtain a standardized effect size value.

The data analysis in this study used a random effects model to accommodate heterogeneity between studies. The effect size value was calculated using Cohen's measure d, which describes the magnitude of the influence of the

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independent variable (the size of the deep learning model) on the bound variable (science learning outcomes). The interpretation criteria for effect size refer to the standard set forth by Cohen (1988), namely: $d < 0.2$ is considered a small effect, $0.2 \leq d < 0.5$ is a medium effect, $0.5 \leq d < 0.8$ is a large effect, and $d \geq 0.8$ is a very large effect (very large effect). The use of JASP as an analysis tool allows for systematic visualization through forest plots, funnel plots, as well as publication bias tests such as Egger's Test, which adds to the reliability of the interpretation of results. With this approach, it is hoped that the research can make an empirical contribution to the selection of optimal AI models in the context of science education at various levels.

3. Results and Discussions

The Based on the results of data search through the database, 12 studies/articles met the inclusion criteria. The effect size and error standard can be seen in Table 2.

Table 2. Effect Size and Standard Error Every Research

Code Journal	Years	Country	Effect Size	Standard Error
JR1	2024	Indonesia	0.81	0.32
JR2	2022	Indonesia	1.10	0.29
JR3	2022	Indonesia	0.82	0.30
JR4	2025	Indonesia	0.99	0.23
JR5	2024	Indonesia	1.04	0.22
JR6	2025	Indonesia	0.44	0.19
JR7	2025	Indonesia	0.28	0.11
JR8	2023	Indonesia	1.82	0.29
JR9	2024	Indonesia	0.67	0.30
JR10	2022	Indonesia	0.61	0.19
JR11	2022	Indonesia	0.82	0.35
JR12	2025	Indoensia	0.81	0.31

Based on Table 2, the effect size value of the 12 studies ranged from 0.44 to 1.82 . According to Borenstein et al., (2007) Of the 12 effect sizes, 6 studies had medium criteria effect sizes and 18 studies (75%) had high criteria effect size values. Furthermore, 12 studies were analyzed to determine an estimation model to calculate the mean effect size. The analysis of the fixed and random effect model estimation models can be seen in Table 3.

Table 3. Residual Heterogeneity Test

Qe	**df**	**p**
37.636	11	< 0.001

Based on Table 3, a Q value of 37.636 was obtained higher than the value of 22.112 with a coefficient interval of 95% and a p value of 0.001 <. The findings can be concluded that the value of 24 effect sizes analyzed is heterogeneously distributed. Therefore, the model used to calculate the mean effect size is a random effect model. Furthermore, checking publication bias through funnel plot analysis and Rosenthal fail safe N (FSN) test (Tamur et al., 2020; Badawi et al., 2022; Ichsan et al., 2023b; Borenstein et al., 2007). The results of checking publication bias with funnel plot can be seen in Figure 2.

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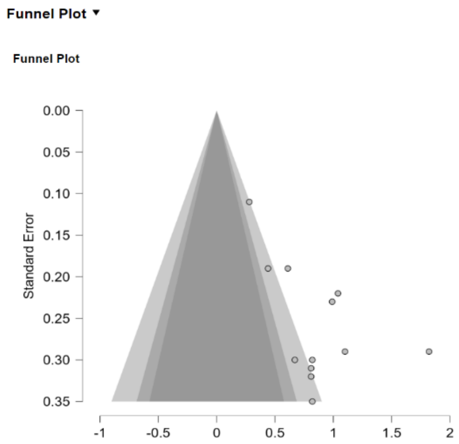

Figure 2. Funnel Plot Standard Error

Based on Figure 2, the analysis of the funnel plot is not yet known whether it is symmetrical or asymmetrical, so it is necessary to conduct a Rosenthal Fail Safe N (FSN) test. The results of the Rosenthal Fail Safe N calculation can be seen in Table 4.

Tabel 4. Fail Safe N

File Drawer Analysis			
	Fail Safe N	Target Significance	Observed Significance
Rosenthal	915	0.050	< 0.001

Based on Table 4, the Fail Safe N value of 915 is greater than the value of 5k + 10 = 5(12) + 10 = 70, so it can be concluded that the analysis of 12 effect sizes in this data is not biased by publication and can be scientifically accounted for. Next, calculate the p-value to test the hypothesis through the random effect model. The results of the summary effect model analysis with the random effect model can be seen in Table 5.

Tabel 5. Pooled Effect Size Test

Estimates	**Standar Error**	**t**	**df**	**p**
0.815	0.114	7.128	11	<0.001

Based on Table 5, it is estimated that there is a positive influence of the deep learning model in science learning with a value of $d = 0.815$; $p < 0.001$ with a high effect size category

Discussion

This is because the complexity of the architecture and the large number of parameters allow the model to capture more complex and diverse data patterns (Devlin et al., 2018). In science learning, especially those based on conceptual knowledge and understanding of scientific texts, the ability of large model semantic representations can increase students' cognitive engagement and improve the accuracy of responses to concept-based questions. In the context of schools with limited technological infrastructure, these models are an ideal alternative. Results of meta-analysis from several studies (e.g. Zhang et al., 2022; Lee & Kim, 2023) shows that small models are still able to have a positive impact on science learning outcomes, especially at the primary and secondary education levels, as long as the model is integrated with appropriate pedagogical strategies (Babu Vimala et al., 2023).

The effect of the size of the deep learning model on science learning outcomes is greater in students at the university level than at the elementary or secondary level. This is suspected because students have a higher digital literacy and science capacity, so they are better able to take advantage of the advanced features of large

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models(Jordan & Mitchell, 2015; Sullivan, 2022). In contrast, elementary and middle school students show better responses to simple learning interfaces, which are typically supported by smaller-sized but fast and responsive deep learning models (Tang et al., 2021). Technology-based science learning requires fast and accurate information processing. Large deep learning models can provide features such as automatic recommendation systems, open-ended answer assessments, and visual-based learning simulations (Wexler et al., 2020). The use of large models in this context allows for a more adaptive learning approach and personalization of content in real time. However, the consequence is the high hardware requirements and technical skills of both teachers and system developers. Therefore, the selection of model sizes must consider the technological readiness and competence of educators in each educational institution (Shahinfar et al., 2020).

Of the 12 journals analyzed, the average value of effect size was in the medium to large category (mean d = 0.815). This shows that in general, the use of deep learning models—both large and small—has a positive impact on science learning outcomes. Studies that used large models tended to show higher effect size values ($d > 0.7$), while small models were in the range d between 0.44 to 1.82. Thus, there is a correlation between the size of the model and the magnitude of the effect on learning outcomes, although other factors such as learning design and material type also play an important role. important for teachers and educational technology developers. In situations where computing resources are limited, the use of small, efficient models can still make a positive contribution to science learning (Chandra et al., 2023; Morgan & Jacobs, 2020). However, in environments with good infrastructure support, large model implementations can maximize the potential of AI-based learning. A hybrid approach that combines the power of large models for initial training and small models for classroom implementation can also be an efficient and inclusive strategic solution (Reichstein et al., 2019). In addition, most of the studies analyzed came from urban contexts or schools with access to high technology, so they are less representative of the conditions of the 3T area. Further research is suggested to examine the effectiveness of model size in the context of hybrid learning, as well as expand the study population to the PAUD or inclusion education level to gain a more comprehensive understanding (Eraslan et al., 2019; Agrawal & Choudhary, 2019).

4. Conclusion

From the results of this study, it is concluded that there is a significant influence of the deep learning model in science learning with an effect size value of 0.915 in the high effect size category. These findings explain that the deep learning model is effectively applied at the elementary school to university education levels. These findings indicate that the selection of the size of the deep learning model in science learning must consider the readiness of the infrastructure, the level of education, and the learning objectives to be achieved. In the context of technological limitations, the use of small models can still be optimized through the right pedagogical integration. In contrast, in institutions with adequate technological support, the use of large models can facilitate the personalization of learning and the improvement of students' scientific literacy more effectively. This study also recommends further exploration of the interaction between model size and digital learning strategies used.

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