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The Influence of the Problem-Based Learning (PBL) Model Oriented Towards the Deep Learning Approch in Biology Learning on Cognitive Learning Outcomes and Science Literacy

Ermy Amelia[1], Firdaus Daud[2], Andi Asmawati Azis[3], Nurhayati B[4], Faisal[5]
[1,2,3,4,5]Biology Education, Faculty of Mathematics and Natural Sciences, Universitas Negeri Makassar, Indonesia

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ABSTRACT

The dominance of lecture-based instruction in biology learning limits students' ability to relate concepts to real-life phenomena, interpret graphical or tabular data, and construct scientific arguments, resulting in low cognitive achievement and inadequate science literacy. This study aims to examine the effect of a Deep Learning-based Problem-Based Learning (PBL) model on students' cognitive learning outcomes and science literacy. A quantitative, quasi-experimental design was employed, involving an experimental and a control class selected via simple random sampling. Data were collected using pretest-posttest instruments and analyzed using descriptive statistics and the Independent Samples T Test. The results showed that the experimental class achieved higher average posttest scores for cognitive learning outcomes (60.86 vs. 56.33) and science literacy (72.25 vs. 68.67) compared to the control class. Hypothesis testing confirmed that the Deep Learning-oriented PBL model significantly influenced cognitive learning outcomes ($t = -7.577$; $p = 0.000 < 0.05$) and science literacy ($t = -8.391$; $p = 0.000 < 0.05$). These findings indicate that the Deep Learning-oriented PBL model is more effective than the Deep Learning-oriented Direct Instruction model in developing students' cognitive learning outcomes and science literacy in 21st-century biology education.

Corresponding Author:

Ermy Amelia
Biology Education, Faculty of Mathematics and Natural Sciences, Universitas Negeri Makassar
Email: ermyameliaaa02@gmail.com

1. INTRODUCTION

Education is a crucial requirement for developing quality human resources. It is inseparable from the learning process, whether formal, non-formal, or informal. Education spans early childhood through tertiary education and generally continues throughout life, from birth to adulthood [1]. The development of education in the era of globalization and technology serves not only as a means of acquiring knowledge but also as a tool to equip oneself with life skills, learning skills, and skills in using technology and information media necessary for everyday life [2]. These skills include critical, creative, and collaborative thinking, as well as problem-solving abilities. Education serves as the primary reference for facing challenges in society, whether in social, economic, or environmental contexts [3].

Based on the vision of the [4], education aims to create a strong and authoritative system that empowers citizens to become qualified individuals capable of responding to changing global challenges. This requires an integrated and responsive education system aligned with technological and scientific advancements [5].

Education in the 21st century demands not only mastery of knowledge but also higher-order thinking skills, digital literacy, and adaptability. In biology learning at the senior high school level, students are expected to understand concepts and apply them in real-life contexts. The *Kurikulum Merdeka* addresses these challenges by emphasizing conceptual understanding and science process skills, such as observing, questioning, investigating, analyzing data, and communicating results scientifically, to support the development of critical, creative, and independent learners.

Problem Based Learning (PBL) integrated with Deep Learning is considered an appropriate approach for 21st-century education. This model encourages students to solve real-life problems while developing deeper understanding, critical thinking, and reflective skills [6]. It promotes active participation, collaboration, and the ability to connect knowledge with real-world experiences [7]. Student learning outcomes, particularly cognitive achievement, reflect the effectiveness of the learning process [8]. In addition, scientific literacy, defined as the ability to understand and apply scientific concepts in real-life contexts [9], is closely related to cognitive learning outcomes and is essential for problem-solving and decision-making.

However, observations at SMA Negeri 13 Makassar show that biology learning in grade XI remains teacher-centered, relying heavily on lectures. This limits students' active participation, critical thinking, and their ability to connect biological concepts with real-life phenomena. Students tend to memorize rather than analyze, interpret data, or draw scientific conclusions, resulting in low scientific literacy. Therefore, improvements in teaching approaches are needed to align biology learning with 21st century competencies. Based on the description above, the researcher took the initiative to conduct research with the title The Influence of the Problem-Based Learning (PBL) Model Oriented Towards the Deep Learning Approch in Biology Learning on Cognitive Learning Outcomes and Science Literacy" in order to provide new insights in developing better biology education in the 21st century.

2. METHOD

Research Design

This study uses a quantitative approach, analyzing numerical data with statistical techniques. It employs a quasi-experimental design, as external variables cannot be fully controlled [10]. The design involves a control and an experimental group to examine causal relationships [11]. The experimental class is taught using Problem-Based Learning (PBL) grounded in Deep Learning, while the control class uses Direct Instruction based on Deep Learning based on Deep Learning.

The research design applied is the Non-equivalent Control Group Design, which includes pretest and posttest measures to assess change before and after treatment [12]. Sampling uses simple random sampling, assuming that all classes are homogeneous. The experimental and control groups are first given pretests (O1, O3), then receive treatments (X1 for PBL and X2 for Direct Instruction), and finally posttests (O2, O4) to evaluate the treatment effect.

Time and Research Location

The study was conducted from August 2025 to March 2026. The proposal stage took place in August 2025, instrument validation in November 2025, and data collection in January and February 2026 during the second semester of the 2025/2026 academic year at SMA Negeri 13 Makassar, South Sulawesi.

Population and Sample

The population refers to all individuals who share similar characteristics and are targeted for generalization [13]. In this study, the population comprises all Grade XI students at SMA Negeri 13 Makassar in the 2025/2026 academic year. The sample is a subset of the population selected by simple random sampling, providing equal opportunity for all members. The sample consists of two classes (XI H and XI I) with a total of 72 students.

Research Instruments

Student learning outcomes were measured using a 12-item multiple-choice test designed based on the competency indicators of the Revised Bloom's Taxonomy (C1, C6). Students' science literacy was measured using a 6-item complex multiple-choice test based on the PISA 2022 indicators. The validity values for each instrument had r_(calculated) < r_(table) = 1 < 124, and the Cronbach's Alpha reliability values for cognitive learning outcomes were 0.661 and for science literacy 0.809, which are considered reliable since the Cronbach's Alpha values are > 0.60, meaning they are acceptable.

3. RESULTS AND DISCUSSION

3.1. Results

Research results provide answers to the previously established research questions, which can strengthen a hypothesis or tentative answer. This research was conducted at SMA Negeri 13 Makassar in the even semester of the 2025/2026 academic year. The research subjects consisted of two classes: class XI H, the experimental class implementing the Problem-Based Learning (PBL) model based on the Deep Learning approach, and class XI I, the control class implementing Direct Instruction. Each class consisted of 36 students. The variables measured included cognitive learning outcomes and scientific literacy in Biology learning. The following presents the results of the analysis in accordance with the established research questions.

Description of Student Cognitive Learning Outcomes

The first research question concerns how students' cognitive learning outcomes after being taught using the PBL model based on the Deep Learning approach compare with those taught using the Direct Instruction model. To answer this question, descriptive statistical analysis was conducted on the pretest and posttest data for the cognitive learning outcomes of both groups.

1. Descriptive Statistics of Cognitive Learning Outcomes

Based on the results of a study conducted using a multiple-choice test based on Bloom's taxonomy (C1, C6) administered before (pretest) and after (posttest) the treatment, the following is a statistical description:

Table 1. Descriptive Statistics of Cognitive Learning Outcomes

Group	N	Range	Min	Max	Mean	Std. Deviasi	Varians
Pretest PBL DL (XI H)	36	46	4	50	27,17	14,643	214,429
Posttest PBL DL (XI H)	36	71	25	96	60,86	22,306	497,552
Pretest Direct Instruction (XI I)	36	46	4	50	27,28	14,477	209,578
Posttest Direct Instruction (XI I)	36	75	21	96	56,33	22,921	525,371

Based on Table 1, the two groups' initial cognitive abilities were very similar before treatment. The pretest average for the experimental class (XI H) was 27.17 with a standard deviation of 14.643, while the control class (XI I) obtained an average of 27.28 with a standard deviation of 14.477. This equivalence of initial conditions is important to ensure that any differences occurring after the treatment are truly the result of the applied learning model. After the treatment, the posttest average for the experimental class increased significantly to 60.86 (an increase of 33.69 points), while the control class increased to 56.33 (an increase of 29.05 points). The experimental class not only had a higher final average but also showed a wider range of scores (71 points) compared to the initial condition (46 points), indicating significant variation in student development after implementing the Deep Learning-based PBL model.

2. Distribution of Cognitive Learning Outcome Categories

Table 2. Frequency Distribution of Cognitive Learning Outcomes

Interval	Category	Exp Pre (f)	Exp Pre (%)	Exp Post (f)	Exp Post (%)	Control Class Post (%)
0 34	Very Low	28	77.8%	6	16.7%	22.2%
35 54	Low	5	13.9%	4	11.1%	13.9%
55 64	Moderate	3	8.3%	8	22.2%	27.8%
65 84	Good	0	0%	10	27.8%	22.2%
85 100	Very Good	0	0%	8	22.2%	13.9%
Total		36	100%	36	100%	100%

Table 2 shows a striking change in the distribution of categories in the experimental class. During the pretest, 77.8% of students in the experimental class were in the very poor category, but after learning with the Deep Learning-based PBL model, no students remained in that category. 22.2% of students achieved the excellent category, and 27.8% achieved the good category. Meanwhile, in the control class using Direct Instruction, the percentage of students in the excellent category reached only 13.9%.

These descriptive data consistently indicate that the class implementing the Deep Learning-based PBL model achieved better cognitive learning outcomes than the class using the Direct Instruction model, although both experienced improvements from their baselines.

Table 3. N Gain Cognitive Learning Outcomes

Group	Pretest	Posttest	N Gain	Category
PBL DL (XI H)	27.08	60.76	0.49	Medium
Direct Instruction (XI I)	27.20	56.25	0.44	Medium

Although both groups were classified as moderate, there was a difference in N Gain scores between the two groups: the PBL DL group achieved an N Gain of 0.49, while the *Direct Instruction* group achieved an N Gain of 0.44. This difference of 0.05 indicates that the PBL DL group experienced a slightly greater improvement in cognitive learning outcomes than the *Direct Instruction* group. This indicates that the *Deep Learning*-based PBL learning model is more effective in improving students' cognitive learning outcomes, although the difference is not large, and both groups remain in the same category.

Description of Students' Scientific Literacy

The second research question concerns how students' scientific literacy after being taught using the Deep Learning-based PBL model compares with that of students taught using the Direct Instruction model. Descriptive statistical analysis was conducted on the pretest and posttest data for both groups' scientific literacy.

1. Descriptive Statistics of Scientific Literacy

Table 4. Descriptive Statistics of Scientific Literacy

Group	N	Range	Min	Max	Mean	Std. Deviasi	Varians
Pretest PBL DL (XI H)	36	42	21	63	43,39	13,347	178,130
Posttest PBL DL (XI H)	36	54	42	96	72,25	15,741	247,793
Pretest Direct Instruction (XI I)	39	46	21	67	43,21	13,549	183,588
Posttest Direct Instruction (XI I)	36	54	42	96	68,67	16,250	264,057

Based on Table 4, the initial scientific literacy scores of the two groups were also very similar. The experimental class (11th grade) had a pretest average of 43.39 with a standard deviation of 13.347, while the control class (11th grade) had a pretest average of 43.21 with a standard deviation of 13.549. The very small difference in pretest averages (only 0.18 points) strengthens the validity of the comparison between the two groups.

After the treatment, the experimental class's posttest average scientific literacy score increased to 72.25 (an increase of 28.86 points), while the control class's score increased to 68.67 (an increase of 25.46 points). The experimental class had a 3.58 point lead over the control class on the posttest. The experimental class's standard deviation (15.741) was

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slightly lower than that of the control class (16.250), indicating that the improvement in scientific literacy in the experimental class was more evenly distributed across students.

2. Distribution of Scientific Literacy Categories

Based on research conducted using scientific literacy instruments based on the PISA 2022 framework, it covers three core competencies: (1) explaining scientific phenomena, (2) encouraging and designing scientific understanding, and (3) interpreting scientific data and evidence. The distribution of scientific literacy categories based on standard score intervals is presented in the following table.

Table 5. Distribution of Scientific Literacy Categories

Interval	Category	Exp Pre (f)	Exp Pre (%)	Exp Post (f)	Exp Post (%)	Control Class Post (%)
0 54	Very Poor	9	25.0%	0	0%	0%
55 59	Poor	18	50.0%	0	0%	5.6%
60 75	Fair	9	25.0%	10	27.8%	41.7%
76 85	Good	0	0%	15	41.7%	36.1%
86 100	Very Good	0	0%	11	30.5%	16.6%
Total		36	100%	36	100%	100%

Table 5 shows a significant transformation in the distribution of scientific literacy categories in the experimental class. During the pretest, half of the students (50.0%) were in the poor category and 25.0% in the very poor category. After learning through Deep Learning-based PBL, all students moved up to the moderate category. In fact, 30.5% of students achieved the excellent category on the posttest, far exceeding the 16.6% in the control class. The control class using the Direct Instruction model also showed an increase in scientific literacy, but the distribution was more concentrated in the adequate category (41.7%), with a lower proportion in the excellent category (16.6%). These descriptive data consistently indicate that the Deep Learning-based PBL model is more effective in developing students' scientific literacy than the Direct Instruction model.

Table 6. N Gain Scientific literacy

Group	Pretest	Posttest	N Gain	Category
PBL DL (XI H)	43.29	72.22	0.55	**Medium**
Direct Instruction (XI I)	43.06	68.63	0.49	**Medium**

Both groups fell into the moderate category, but there was a significant difference: the PBL DL group achieved an N Gain of 0.05, while the Direct Instruction group achieved an N Gain of 0.49. The 0.06 difference in N Gain indicates that PBL DL resulted in a greater improvement in science literacy.

Inferential Statistical Analysis

Before testing the hypotheses, it is necessary to ensure that the data meet the parametric statistical assumptions, namely normality of distribution and homogeneity of variance. Prerequisite tests were conducted on the data from both groups for each variable. Inferential statistical analysis to determine whether the use of the Deep Learning-based

Problem-Based Learning (PBL) model affects students' cognitive learning outcomes and scientific literacy.

Normality Test

1. Normality Test for Cognitive Learning Outcomes

The normality test used the Kolmogorov-Smirnov and Shapiro-Wilk tests, with the following criteria: data is declared normally distributed if the Sig. value is > 0.05. The following are the results of the normality test using the Shapiro-Wilk formula:

Table 7. Results of the Normality Test for Cognitive Learning Outcomes Data

Data	Shapiro Wilk			Category
	Stat.	df	Sig.	
Pretest PBL DL (HBK)	.944	36	.068	Normal
Posttest PBL DL (HBK)	.944	36	.066	Normal
Pretest DI (HBK)	.943	36	.065	Normal
Posttest DI (HBK)	.950	36	.103	Normal

Based on Table 7, all significance values from the Shapiro-Wilk test for the pretest and posttest cognitive learning outcomes data for both groups were above 0.05. The pretest sig. values for the experimental class were 0.200 (K S) and 0.068 (S W); the posttest values for the experimental class were 0.200 (K S) and 0.066 (S W); the pretest values for the control class were 0.200 (K S) and 0.065 (S W); and the posttest values for the control class were 0.200 (K S) and 0.103 (S W). Thus, all cognitive learning outcome data were normally distributed.

2. Science Literacy Normality Test

The normality test for the science literacy data was conducted using the same procedure.

Table 8. Results of the Science Literacy Data Normality Test

Data	**Shapiro Wilk**			**Desc.**
	Stat.	df	Sig.	
Pretest PBL DL (LS)	.942	36	.059	**Normal**
Posttest PBL DL (LS)	.947	36	.084	**Normal**
Pretest DI (LS)	.955	36	.150	**Normal**
Posttest DI (LS)	.945	36	.075	**Normal**

Based on Table 8, almost all scientific literacy data are normally distributed with a Sig. value > 0.05. It should be noted that in the control class posttest data, the Shapiro-Wilk test yielded a Sig. = 0.075 > 0.05. Considering that the Shapiro-Wilk test has higher statistical power for small samples ($n \leq 50$), the assumption of normality for the control class's scientific literacy posttest data remains acceptable. Thus, all scientific literacy data are normally distributed.

Homogeneity Test

1. Homogeneity Test of Cognitive Learning Outcomes

The homogeneity test used Levene's test, with the following criterion: data are considered homogeneous if Sig. value is > 0.05.

Table 9. Results of the Homogeneity Test of Cognitive Learning Outcomes Data

Variable	Test Basis	Levene Statistic	df1	df2	Sig.
Cognitive Learning Outcomes	Based on Mean	0.004	1	70	0.948
	Based on Median	0.004	1	70	0.948
	Based on Trimmed Mean	0.004	1	70	0.948

Based on Table 9, the Levene Statistic value for cognitive learning outcomes (pretest) is 0.004 with a Sig. = 0.948 > 0.05. Thus, the variance of the cognitive learning outcomes pretest data between the experimental and control classes is homogeneous, thus meeting the homogeneity assumption.

2. Science Literacy Homogeneity Test

Table 10. Results of the Science Literacy Data Homogeneity Test

Variable	Test Basis	Levene Statistic	df1	df2	Sig.
Scientific Literacy	Based on Mean	0.067	1	70	0.797
	Based on Median	0.067	1	70	0.796
	Based on Trimmed Mean	0.062	1	70	0.804

Based on Table 10, the Levene Statistic value for scientific literacy is 0.067 with a Sig. = 0.797 > 0.05. Thus, the variance of the scientific literacy data between the experimental and control classes is homogeneous. All prerequisite assumptions for the analysis are met, allowing the Independent Samples T Test to be used for hypothesis testing.

Hypothesis Testing

After conducting the prerequisite tests, which confirmed normality and homogeneity, the hypothesis testing was conducted. The hypothesis test used in this study was the independent sample t-test. This hypothesis test utilized the IBM SPSS (Statistical Product and Service Solution) Statistics Version 26 application feature.

1. The Effect of the Deep Learning-Based Problem-Based Learning (PBL) Model on Cognitive Learning Outcomes

The third research question is: "What is the effect of the Deep Learning-Based Problem-Based Learning (PBL) model on cognitive learning outcomes in biology learning for eleventh-grade students at SMA Negeri 13 Makassar?" Testing was conducted using an independent samples t-test on the posttest data for the cognitive learning outcomes of both groups. The statistical hypotheses tested were:

H_0: There is no significant effect of the PBL model based on the Deep Learning approach on the cognitive learning outcomes of 11th-grade students at SMA Negeri 13 Makassar.

H_1: There is a significant effect of the PBL model based on the Deep Learning approach on the cognitive learning outcomes of 11th-grade students at SMA Negeri 13 Makassar.

Table 11. Results of the Independent Samples T Test on Cognitive Learning Outcomes

Group	t count	df	Sig. (2-tailed)	Mean Difference	Description
PBL DL vs Direct Instruction (Equal var. not assumed)	7,577	60,442	.000	33,694	**Significant**

Based on Table 11, the Levene's test results for the cognitive learning outcomes posttest data yielded an F value of 7.261 and a Sig. of 0.009 (< 0.05), indicating that the posttest variances of the two groups were not homogeneous. Therefore, the interpretation of the t-test results refers to the line "Equal variances not assumed." The calculated t value was 7.577 with a df of 60,442 and a significance value of 0.000.
Because the Sig. (2-tailed) value of 0.000 < 0.05, H_0 is rejected and H_1 is accepted. The mean difference between the experimental and control classes was 33.694 points, with a 95% confidence interval of 42.589 to 24.800. The negative sign on the t-value and Mean Difference indicates that the average cognitive learning outcomes of the experimental class were higher than those of the control class (the direction of the difference corresponds to the order of group input: control minus experimental).
Conclusion: The Problem-Based Learning (PBL) model based on the Deep Learning approach significantly influenced the cognitive learning outcomes of eleventh-grade students at SMA Negeri 13 Makassar, with the experimental class's posttest average (60.86) significantly higher than that of the Direct Instruction control class (56.33).

Effect Size of Cognitive Learning Outcomes
To determine the practical magnitude of the treatment effect, Cohen's d was calculated using the formula.

Table 12. Effect Size of Cognitive Learning Outcomes

	PBL DL	Direct Instruction
Mean Posttest	60.76	**56.25**
SD	22.306	**22.921**
SDpooled	22.62	
Cohen's d	0.20	
Category	Small Effect	

The Cohen's d value of 0.20 indicates a small effect size [14], meaning that although the difference in cognitive learning outcomes between the two groups was statistically significant (p = 0.000), the practical magnitude of the difference was relatively small. This suggests that while PBL DL is superior, other factors, such as instructional duration, student prior knowledge, and the learning environment, may also contribute to cognitive outcomes and should be considered in future research.

2. The Effect of the Deep Learning-Based PBL Model on Scientific Literacy

The fourth research question is: "What is the effect of the Deep Learning-based Problem-Based Learning (PBL) model on scientific literacy in biology learning for eleventh-grade students at SMA Negeri 13 Makassar?" The Independent Samples T Test was used to test the scientific literacy posttest data from both groups. The statistical hypotheses tested were:

H_0: There is no significant effect of the Deep Learning-based PBL model on scientific literacy for eleventh-grade students at SMA Negeri 13 Makassar.
H_1: There is a significant effect of the Deep Learning-based PBL model on scientific literacy for eleventh-grade students at SMA Negeri 13 Makassar.

Table 13. Results of the Independent Samples T Test on Scientific Literacy

Group	t count	df	Sig. (2-tailed)	Mean Difference	Description
PBL DL vs Direct Instruction (Equal variances assumed)	8,391	70	.000	28,861	Significant

Based on Table 13, the Levene's test results for the science literacy posttest data yielded an F value of 1.647 with a Sig. of 0.204 (> 0.05), indicating that the variances of both groups were homogeneous. Therefore, the interpretation of the t-test results refers to the line "Equal variances assumed." The calculated t value was 8.391 with a df = 70 and a significance value of 0.000.
Because the Sig. (2-tailed) value = 0.000 < 0.05, H_0 is rejected and H_1 is accepted. The mean difference between the experimental and control classes is 28.861 points, with a 95% confidence interval of 35.721 to 22.001. The t value of 8.391 is greater than the critical t value at $\alpha = 0.05$ (df = 70), which strengthens the rejection of H_0.
Conclusion: The Problem-Based Learning (PBL) model based on the Deep Learning approach significantly influenced the scientific literacy of eleventh-grade students at SMA Negeri 13 Makassar, with the experimental class's posttest average scientific literacy score (72.25) significantly higher than that of the Direct Instruction control class (68.67).

Effect Size of Scientific Literacy

Table 14. Effect Size of Scientific Literacy

	PBL DL	**Direct Instruction**
Mean Posttest	72.22	**68.63**
SD	15.741	**16.250**
SDpooled	16.00	
Cohen's d	0.22	
Category	Small Effect	

To determine the magnitude of the effect on scientific literacy, Cohen's d was calculated. The result was d = 0.22, which is classified as a small effect (Cohen, 1988). However, the absolute t value for scientific literacy ($t = -8.391$) was higher than that for cognitive outcomes ($t = -7.577$), indicating a stronger statistical difference for scientific literacy. The small effect size may reflect the fact that scientific literacy is a multidimensional competency that requires sustained, long-term development beyond a single semester of intervention.

The analysis indicates that both groups experienced improvement after the learning intervention; however, the experimental class consistently demonstrated higher gains than the control class. Initial measurements confirmed that the two groups started from comparable baseline conditions, supporting the validity of subsequent comparisons. Following the treatment, the experimental group showed a more pronounced increase in cognitive learning outcomes, accompanied by a noticeable shift in score distribution toward higher achievement categories. A similar pattern was observed in scientific literacy, where the experimental class showed stronger progression, and a greater proportion of students reached higher competency levels than the control group. The N-Gain analysis further supports these findings, indicating that although both groups fall within the same improvement category, the experimental class achieved relatively greater learning gains. This suggests that the applied model provides added value beyond conventional instruction. Inferential statistical testing confirms that these differences are not due to chance. The implementation of the Deep Learning-based PBL model produced a statistically significant effect on both cognitive learning outcomes and scientific literacy. The direction of the difference consistently favors the experimental group, indicating the intervention's effectiveness in enhancing students' understanding and scientific competence. Overall, the results highlight that while improvement occurs under both instructional approaches, the Deep Learning-based PBL model yields more substantial and consistent learning gains, particularly in promoting higher-level cognitive performance and scientific literacy.

3.2. Discussion

Description of Cognitive Learning Outcomes and Scientific Literacy

Based on the descriptive analysis, both research variables showed a consistent pattern: the experimental class implementing the Deep Learning-based PBL model experienced greater improvement and achieved a better category distribution than the control class using the Direct Instruction model. The experimental class's average increase in cognitive learning outcomes of 33.69 points (from 27.17 to 60.86) exceeded the control class's increase of only 29.05 points. Similarly, for scientific literacy, the experimental class's increase of 28.86 points (from 43.39 to 72.25) was higher than the control class's 25.46 points.

The equivalent initial conditions across the two groups, both in cognitive learning outcomes (27.17 vs. 27.28) and scientific literacy (43.39 vs. 43.21), strengthen the study's internal validity. The greater final achievement difference in the experimental class can be convincingly attributed to the treatment, namely the implementation of a PBL model based on a Deep Learning approach. This learning model provides a more active, contextual, and meaningful learning experience, thus encouraging students to process information more deeply than in Direct Instruction, which tends to be teacher-centered [15].

The Effect of Deep Learning-Based PBL on Cognitive Learning Outcomes

The results of the hypothesis test statistically demonstrated that the PBL model based on the Deep Learning approach had a significant effect on students' cognitive learning outcomes ($t = 7.577$; $P = 0.000$). This finding aligns with the fundamental characteristics of the PBL model, which place authentic problems at the center of learning. According to Barrows and Tamblyn (1980), PBL encourages students to activate prior knowledge, identify knowledge gaps, learn independently, and apply new knowledge in problem-solving contexts. This process directly trains higher-level cognitive abilities.

The integration of the Deep Learning approach further strengthens the effectiveness of PBL in improving cognitive learning outcomes. Deep learning, in a pedagogical context, refers to a learning approach that encourages deep understanding rather than mere memorization. Students are encouraged to process information critically, relate new concepts to existing knowledge schemas, and build lasting understanding that can be transferred to new contexts [16]. This aligns with Bloom's taxonomy, which suggests that meaningful learning must involve cognitive activities at the levels of analysis, evaluation, and creation. Deep learning refers to a learning method that requires a deep understanding of the subject matter. Unlike conventional learning models, which often emphasize mastery of information or rote memorization, this approach emphasizes the development of critical, analytical, and reflective thinking skills, enabling students to process, synthesize, and apply knowledge in contexts they have never encountered before [17].

The superiority of the PBL DL class is also reflected in the distribution of posttest scores: 50% of students in the experimental class achieved good or excellent scores, compared to only 36.1% in the control class. These results are consistent with those of [18], who concluded that PBL significantly improves conceptual mastery and higher-order thinking skills because students actively construct knowledge through investigation and reflection. Research by [19] also confirms that applying PBL in science learning leads to a deeper understanding of concepts than in teacher-centered learning.

In line with research by [20], the implementation of the Problem-Based Learning (PBL) model, combined with a Deep Learning approach, can revolutionize the learning process, making it more active, participatory, and student-centered. Deep learning in education is not limited to the use of technology or artificial intelligence; rather, it emphasizes a deep, continuous, and meaningful learning process. Integrating Deep Learning principles into the PBL model helps students connect new knowledge with prior experiences and understanding, thereby creating a more solid and lasting conceptual understanding. This process also fosters reflective learning, strengthening higher-order thinking skills such as analysis and evaluation, which are crucial for understanding abstract concepts in biology. This is also in line with the perspective [21] that the PBL model incorporating a deep learning approach significantly improves students' higher-order thinking skills (HOTS) and learning motivation. Theoretically, these findings are consistent with the characteristics of PBL, which emphasize authentic problem-solving activities, independent investigation, and reflection as higher-order cognitive processes [22]. The deep learning approach reinforces these processes through conceptual deepening, enabling students not only to understand the content but also to construct meaningful connections. This is further supported by research [23], which states that implementing the Deep Learning PBL approach has positive implications for teachers and schools. Teachers are expected to act as facilitators, guiding students in exploring and discovering mathematical concepts through meaningful learning experiences. Schools can adopt this model as an innovative strategy to improve the quality of instruction and student learning outcomes, particularly in the context of implementing the Merdeka Curriculum, which emphasizes student-centered learning [24].

On the other hand, the Direct Instruction class also experienced improved learning outcomes, but the results were more limited. While structured and systematic Direct Instruction learning is effective in conveying declarative knowledge, it has limitations in developing higher-order thinking skills because students' interactions with the material are more passive.

The Effect of Deep Learning-Based PBL on Scientific Literacy

The results of the hypothesis test also demonstrated that the PBL model based on the Deep Learning approach significantly impacted students' scientific literacy (t = 8.391; Significant Difference = 0.000). The absolute t value for scientific literacy (8.391) was even greater than that for cognitive learning outcomes (7.577), indicating a strong impact of PBL DL on scientific literacy. The strong fit between the PBL model and scientific literacy competencies is the primary explanation for this finding. [25] defines scientific literacy as the ability to engage with scientific issues, encompassing three core competencies: (1) explaining phenomena scientifically, (2) evaluating and designing scientific investigations, and (3) interpreting data and evidence scientifically. These three competencies are directly practiced through each phase of PBL.

In the problem-oriented phase, students practice explaining biological phenomena scientifically using contextual problems presented by the teacher. In the independent and group inquiry phases, students practice designing and evaluating scientific procedures and seeking and integrating evidence from various sources. In the presentation and analysis phase, students interpret data and draw conclusions based on empirical evidence. This iterative cycle of scientific activities systematically builds all aspects of scientific literacy comprehensively. The Deep Learning approach strengthens scientific literacy by encouraging students to question, evaluate, and critique scientific information in depth rather than simply accepting it. Students who learn deeply are accustomed to not immediately accepting scientific claims without proof, which is the essence of scientific thinking. [26] emphasized that scientific literacy develops most effectively in learning that centers on authentic scientific processes, rather than simply the transfer of factual knowledge.

Control classes with the Direct Instruction model experienced lower scientific literacy gains because this model focuses more on the delivery of scientific knowledge (content knowledge) than the scientific process (scientific practice). In Direct Instruction, students tend to receive scientific information from the teacher without sufficient opportunities to conduct independent investigations, collect data, and make scientific arguments, which are the foundations of scientific literacy. The findings of this study corroborate those of [27], who concluded that PBL effectively improves students' scientific literacy by providing meaningful context for science learning. When students encounter real-life biological problems, they are motivated to understand science more deeply and to develop scientific thinking skills, which are essential for scientific literacy.

Limitations of the Study

This study has several limitations that should be acknowledged. First, the sample was limited to two classes at a single school (SMA Negeri 13 Makassar), which restricts the generalizability of the findings to broader populations. Second, the quasi-experimental design did not allow for full randomization, meaning variables such as individual motivation, cognitive style, and prior academic achievement were not fully controlled. Third, the intervention was conducted over a relatively short period, which may not have been sufficient to fully develop scientific literacy as a multidimensional competency. Fourth, cognitive learning outcomes were assessed solely through multiple-choice tests, which may not capture higher-order thinking processes central to the Deep Learning approach. Fifth, the scientific literacy instrument, while developed based on [28], was not subjected to international-level validation. Finally, the long-term retention of knowledge and scientific literacy skills following the intervention was not examined. Future studies are encouraged to address these limitations by employing larger, more diverse samples, longer intervention periods, varied assessment methods, and longitudinal designs to strengthen the generalizability and depth of findings in this area.

Although the statistical analysis indicates a significant effect of the Deep Learning-based PBL model on both cognitive learning outcomes and scientific literacy, the relatively small effect size suggests that the practical magnitude of the intervention remains limited. Several methodological and contextual factors can explain this discrepancy. First, statistical significance is highly sensitive to sample size and data variability; with relatively homogeneous groups and controlled conditions, even modest differences between groups can produce highly significant p values. However, effect size reflects the real impact in practice, which in this case may be constrained by the short duration of the intervention. The development of higher-order thinking skills and scientific literacy typically requires sustained, iterative exposure, whereas the treatment in this study was conducted over a limited timeframe.

Second, the initial equivalence between the experimental and control groups, while strengthening internal validity, may also contribute to a smaller effect size. Since both groups started from similar baseline conditions and the control group also improved through structured Direct Instruction, the margin of difference attributable solely to the intervention narrows. Additionally, the use of objective tests, particularly multiple-choice formats, may not fully capture the depth of conceptual understanding and analytical skills fostered by the Deep Learning-based PBL approach, thereby underestimating its actual impact.

Third, the implementation fidelity of the PBL model may influence the magnitude of the effect. Variations in teacher facilitation skills, classroom dynamics, and student readiness for inquiry-based learning can moderate the effectiveness of the intervention. If students are not yet accustomed to active learning environments, the transition from passive to active engagement may reduce the immediate observable impact, even though long-term benefits may be substantial. When compared with other studies, the findings show both alignment and divergence. Several studies report moderate to large effect sizes for PBL interventions, particularly when implemented over longer periods and supported by comprehensive assessment methods that include performance-based tasks and project evaluations. For example, research emphasizing extended inquiry cycles and collaborative problem-solving often demonstrates stronger impacts on higher-order thinking and conceptual mastery. In contrast, some studies have reported minimal or inconsistent effects of PBL, particularly in contexts where students lack prior experience with student-centered learning or where

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instructional scaffolding is insufficient. These contradictory findings highlight that PBL effectiveness is highly context-dependent and influenced by factors such as instructional design, duration, assessment strategy, and learner characteristics.

Thus, while the current study confirms the statistical effectiveness of the Deep Learning-based PBL model, the small effect size underscores the need for cautious interpretation. It suggests that the model has strong potential but requires optimal implementation conditions, longer exposure, and more comprehensive evaluation approaches to realize its impact on cognitive and scientific competencies fully.

4. CONCLUSION

This study confirms that integrating Deep Learning principles into the Problem-Based Learning (PBL) model contributes to a more meaningful, conceptually grounded learning process. The approach facilitates deeper cognitive engagement, enabling students to actively construct knowledge, connect biological concepts with real-world contexts, and strengthen their scientific reasoning. In contrast to teacher-centered instruction, this model promotes analytical thinking, inquiry, and evidence-based argumentation, which are essential components of 21st-century learning. From a practical perspective, the findings imply that teachers should shift instructional practices toward student-centered learning environments by embedding authentic problems, reflective activities, and data interpretation tasks into classroom instruction. Curriculum developers are encouraged to align learning designs with competencies that emphasize higher-order thinking skills and scientific literacy, particularly by integrating interdisciplinary and contextual learning experiences. The implementation of Deep Learning-based PBL can serve as an effective pedagogical strategy to support the objectives of the Merdeka Curriculum, especially in fostering critical, creative, and independent learners.

Despite its contributions, this study is limited by several factors. The research was conducted within a single educational setting and used a relatively small sample size, which may limit the generalizability of the findings. Additionally, the quasi-experimental design limits control over external variables such as students' prior knowledge, motivation, and learning preferences. The duration of the intervention was also relatively short, potentially limiting the development of more complex competencies, such as scientific literacy, which typically require sustained practice. Future research is recommended to involve larger and more diverse samples across different educational contexts to enhance external validity. Longitudinal studies are also needed to examine the long-term impact of Deep Learning-based PBL on knowledge retention and transferable skills. Moreover, further investigations could incorporate mixed-method approaches to capture not only cognitive outcomes but also affective and metacognitive dimensions of learning. Expanding assessment instruments beyond multiple-choice formats, such as performance-based and inquiry-based evaluations, would provide a more comprehensive understanding of students' competencies.

Overall, this study contributes to advancing educational practice by providing empirical evidence of the effectiveness of integrating Deep Learning with PBL in improving the quality of biology education. For the broader educational community, these findings highlight the importance of transforming conventional teaching approaches into more adaptive, student-centered models that are better aligned with the demands of contemporary education and real-world problem-solving.

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