Kognitif
Jurnal Riset HOTS Pendidikan Matematika
Volume - 6 No - 3 2026 Page 1167 – 1181
ISSN 2776-9704 P-ISSN 2776-9984
https://doi.org/10.51574/kognitif.v6i3.5283

Application of a Deep Learning Approach to Mathematics Learning Outcomes in the Probability Unit for Ninth-Grade Students

Fitria Andyasti Rahayu Pranata, Nani Ratnaningsih, Satya Santika

How to cite: Pranata, F. A. R., Ratnaningsih, N., & Santika, S. (2026). Application of a Deep Learning Approach to Mathematics Learning Outcomes in the Probability Unit for Ninth-Grade Students. *Kognitif: Jurnal Riset HOTS Pendidikan Matematika*, *6*(3), 1167–1181. https://doi.org/10.51574/kognitif.v6i3.5283

To link to this artcle: https://doi.org/10.51574/kognitif.v6i3.5283

Opened Access Article

Published Online on 14 August 2026

Submit your paper to this journal

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

Application of a Deep Learning Approach to Mathematics Learning Outcomes in the Probability Unit for Ninth-Grade Students

Fitria Andyasti Rahayu Pranata[1], Nani Ratnaningsih[1], Satya Santika[1*]

[1]Mathematics Education Study Program, Faculty of Teacher Training and Education, Universitas Siliwangi

Article Info

Article history:

Received Jun 07, 2026
Accepted Aug 09, 2026
Published Online Aug 14, 2026

Keywords:

Deep Learning Approach
Higher-Order Thinking
Mathematics Learning Outcomes
Minimum Mastery Criterion
Probability

ABSTRACT

This study aimed to determine whether the mathematics learning outcomes of ninth-grade students on probability material after the implementation of a deep learning approach had achieved the Minimum Mastery Criterion (MMC). The study was motivated by the importance of developing students' conceptual understanding, critical thinking skills, and active participation in mathematics learning through meaningful and student-centered instruction. The deep learning approach was expected to help students develop higher-oerder thinking skills, particularly in applying, analyzing, and evaluating probability concepts. This research employed a pre-experimental method using a One-Shot Case Study design. The population of the study consisted of all ninth-grade students at SMP Negeri 8 Tasikmalaya. The sample was selected using the cluster random sampling technique, in which one class was randomly chosen as the research sample. The instrument used in this study was a mathematics learning outcomes test on probability material developed based on cognitive indicators, namely C3 (applying), C4 (analyzing), and C5 (evaluating). The test was designed to measure students' understanding and problem-solving abilities related to probability topics. The data were analyzed using descriptive and inferential statistics techniques. Descriptive statistics were used to describe students' mathematics learning outcomes, while inferential statistics were applied to test the research hypothesis. The hypothesis testing technique used in this study was the One-Sample t-Test to determine whether the average score of students' learning outcomes had achieved the established MMC score of 80. The results showed that the average mathematics learning outcome score of the students was 73, which was below the established Minimum Mastery Criterion. Therefore, it can be concluded that the mathematics learning outcomes of ninth-grade students on probability material after the implementation of the deep learning approach had not yet achieved the Minimum Mastery Criterion.

Corresponding Author:

Satya Santika,
Mathematics Education Study Program,
Faculty of Teacher Training and Education,
Universitas Siliwangi,
Jl. Siliwangi No. 24, Kahuripan, Tawang District, Tasikmalaya City, West Java 46115, Indonesia
satyasantika@unsil.ac.id

Introduction

Learning outcomes serve as a critical indicator of the extent to which educational objectives have been achieved. In mathematics education, the cognitive domain is frequently the primary focus because it directly relates to students' ability to comprehend concepts, apply formulas, and solve problems logically and systematically. When students' cognitive learning outcomes are suboptimal, this signals obstacles in the learning process arising from internal factors such as student motivation and interest, as well as external factors such as the instructional method applied and the availability of supporting facilities (Oktaviani et al., 2020).

At the national level, low mathematics learning outcomes remain a clearly visible issue within Indonesia's educational system. Research consistently shows that many students struggle to understand foundational concepts, perform calculations, and solve problems requiring logical reasoning and analysis. Siregar et al. (2024) found that students' mathematics learning outcomes remain low because their conceptual understanding has not adequately developed and the learning process does not sufficiently encourage critical thinking. Similar findings by Dewi et al. (2019) indicated that students frequently make errors in mathematics because they struggle to understand and connect concepts.

This problem is also evident at SMP Negeri 8 Tasikmalaya, particularly in the probability topic. Based on the daily assessment (ulangan harian) scores from the 2024/2025 academic semester, the overall class average was 74.49 with a mastery rate of approximately 36.39%, both of which fall below the school's Minimum Mastery Criterion (MMC) of 80. Most students encountered difficulties in: (1) analysing the results of probability experiments, (2) determining the relative frequency of an event, (3) understanding the relationship between relative frequency and theoretical probability, and (4) solving contextual problems requiring higher-order thinking. These difficulties map directly onto the higher-order cognitive levels assessed in this study: determining relative frequency reflects applying (C3), examining the relationship between relative frequency and theoretical probability reflects analysing (C4), and judging the adequacy of data for estimating probability reflects evaluating (C5). Probability is therefore a suitable topic for a Deep Learning approach, because it is inherently abstract and prone to rote memorisation, causing many students to memorise formulas without genuinely understanding the underlying concepts (Riana & Fitrianna, 2021; Finariya et al., 2023).

Preliminary observations indicated that although the school had adopted Problem Based Learning (PBL), its implementation in probability lessons had not been fully supported by an approach that encourages deep understanding. Specifically, the problems presented were often not sufficiently contextual, group discussions did not run optimally so that not all students were actively engaged, and lessons rarely included a reflection stage; instruction tended to be dominated by the teacher and followed procedural scientific steps culminating in formula application, leaving students insufficient opportunity to explore problems in depth or reflect on their thinking. As a result, students' higher-order thinking skills, particularly applying (C3), analysing (C4), and evaluating (C5) as defined by the revised Bloom's Taxonomy, remained underdeveloped, directly affecting learning outcomes. This concern is not unique to probability. Bayu et al. (2026), writing in this journal, likewise report that conventional instruction often leaves students' higher-order thinking underdeveloped and argue for learning designs that deliberately target analysis and evaluation.

To address this challenge, this study applies the Deep Learning approach to probability learning. In the context of education, Deep Learning refers to a student-centred approach that emphasises deep conceptual understanding through active engagement, real-world relevance, and higher-order thinking skills development (Wijayanto, 2025). According to Anggraena et al.

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

(2025), this approach is built on three core learning principles: (1) mindful learning, learning with full awareness, reflection, and conscious engagement; (2) meaningful learning, connecting new knowledge with prior knowledge and real-life contexts; and (3) joyful learning, creating a positive, enjoyable, and motivating learning atmosphere. In this study these three principles constitute the treatment and are operationalised through contextual probability investigations, collaborative experiments, and reflective discussion (see Method). The joyful-learning principle in particular aligns with recent work in this journal by Rahmawati et al. (2026), who found that a joyful learning model improved students' mathematical reasoning, which suggests that positive affect and reasoning gains can develop together.

Previous studies have demonstrated the potential of the Deep Learning approach. Wahyudi (2025) found that students in a Deep Learning class achieved a posttest average of 81.6% compared to 69.2% in the conventional class. Marjiyem (2025) reported an increase in students' conceptual understanding from 24% to 72% after implementing this approach. Bambang et al. (2025) also showed that the Deep Learning approach improved problem-solving ability and learning motivation in mathematics. Consistent international evidence points the same way: Hammadi et al. (2023) found that a deep learning strategy raised secondary students' mathematics achievement above that of a conventional group, and García et al. (2016) showed that a deep approach to learning positively predicts mathematics achievement, whereas a surface approach predicts it negatively. However, these studies differ from the present one in important ways: they were mostly conducted at the senior high school level, addressed general mathematical thinking or algebra rather than probability, and employed comparative or quasi-experimental designs. Internationally, a deep approach to learning has been associated with better learning outcomes (Peng & Chen, 2019) and is theoretically grounded in constructivism (Silalahi et al., 2022), yet evidence on its application to abstract topics such as probability at the junior high school level remains scarce. Studies specifically examining the Deep Learning approach for improving learning outcomes on the probability topic at the junior high school level therefore remain limited.

This study aims to fill this gap by describing the mathematics learning outcomes of Grade IX students on probability material after the implementation of the Deep Learning approach, and by determining, through a one-tailed One-Sample t-Test, whether the class average has reached the school's MMC of 80. Consistent with the One-Shot Case Study design, the objective is limited to assessing achievement of the mastery criterion rather than proving the causal effectiveness of the approach.

Deep Learning Approach

In education, the term Deep Learning does not refer to the machine-learning technique of the same name but to a pedagogical orientation in which students pursue understanding rather than mere reproduction. It is rooted in the long-standing distinction between a deep approach and a surface approach to learning: a deep approach seeks meaning, integrates new ideas with prior knowledge, and monitors one's own understanding, while a surface approach relies on memorisation and reproduction with little reflection (García et al., 2016). Wijayanto (2025) describes the Deep Learning approach as a student-centred process built on active engagement, real-world relevance, and the deliberate development of higher-order thinking, so that learners construct meaning instead of storing procedures.

Within the Indonesian curriculum framework, Anggraena et al. (2025) operationalise the approach through three principles. Mindful learning asks students to work with awareness: to notice what a problem is really asking, to observe patterns in data, and to reflect on the steps they take. Meaningful learning asks them to connect a concept to prior knowledge and to everyday situations, so that the concept has a purpose beyond the worksheet. Joyful learning creates a positive and motivating atmosphere, most often through games, experiments, and collaboration, so that engagement is sustained rather than forced. These principles are not separate activities but overlapping qualities that can be present in the same task.

Empirical studies support the value of this orientation. Hammadi et al. (2023) reported that secondary students taught with a deep learning strategy outperformed a conventionally taught group in mathematics achievement, and Pujawati et al. (2025) argue that the approach is well suited to mathematics because it foregrounds conceptual depth rather than procedural mastery alone. Related student-centred designs in this journal report similar benefits: Juika et al. (2026) found that Problem Based Learning combined with a Teaching at the Right Level approach improved students' conceptual understanding, and Fitriana et al. (2026) reported gains in conceptual understanding from contextual, problem-based instruction. Taken together, this literature frames the Deep Learning approach as a promising route to deeper understanding, while leaving open how it performs on abstract topics such as probability at the junior high school level.

Probability Problems

Probability is widely regarded as one of the more difficult strands of school mathematics. Unlike topics that rest on a single deterministic procedure, probability requires students to reason about uncertainty, to distinguish what happens in a single trial from what tends to happen over many trials, and to hold empirical results and theoretical expectations side by side. Riana and Fitrianna (2021) and Finariya et al. (2023) note that Indonesian junior high school students frequently struggle with probability because instruction emphasises formulas and procedures over meaning, so that students memorise steps without grasping why they work.

A recurring source of difficulty is the relationship between relative frequency and theoretical probability. Students often expect the outcomes of a short experiment to match theoretical values exactly and are puzzled when they do not, a pattern linked to weak intuitions about variability and the law of large numbers (Öçal, 2018). Kazak and Pratt (2021) show that learners tend to confuse real-world experimental data with model-generated expectations, and that coordinating the two perspectives is cognitively demanding. Begolli et al. (2021) further demonstrate that much of the difficulty in probabilistic reasoning traces back to fragile proportional reasoning, since relative frequency is itself a ratio.

These documented difficulties align closely with the three cognitive demands assessed in this study. Determining a relative frequency from given information is an applying (C3) task; comparing an empirical relative frequency with a theoretical probability and explaining the relationship is an analysing (C4) task; and judging which of two data sets better estimates a true probability, with justification, is an evaluating (C5) task. Because these demands sit at the higher levels of the revised Bloom's Taxonomy, probability offers a stringent setting in which to examine whether a Deep Learning approach can move students beyond procedural recall toward genuine reasoning.

Method

Type of Research

This study employed a pre-experimental research design using a One-Shot Case Study. This design was selected because the study aimed to determine whether students' mathematics learning outcomes on probability topics, after the implementation of the Deep Learning

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

approach, achieved the Minimum Mastery Criterion (MMC) established by the school. In this design, a single group of students received the instructional treatment and was subsequently administered a posttest to measure their learning outcomes. The posttest results were then compared with the school's MMC of 80 to determine the level of students' achievement after the intervention (Creswell & Creswell, 2023). It should be emphasised that this design can only indicate whether the posttest results reached the MMC; it cannot establish the causal effect of the Deep Learning approach, because there is no pretest and no comparison class.

Population and Sample

The population of this study consisted of all ninth-grade students at SMP Negeri 8 Tasikmalaya during the 2025/2026 academic year, comprising eleven classes (IX-A to IX-K) with a total of 382 students. Since the subjects had already been organised into permanent classes, the sample was selected using the cluster random sampling technique, in which the sampling unit was a class rather than an individual student (Sugiyono, 2023). One class was drawn at random from the eleven ninth-grade classes, and Class IX-C, consisting of 33 students, was selected as the research sample. All 33 students participated in the learning activities and completed the posttest. The selected class then received mathematics instruction on probability topics through the implementation of the Deep Learning approach.

Instruments

The research instrument was a mathematics learning outcomes test on probability, designed to measure students' cognitive achievement after participating in learning activities using the Deep Learning approach. The test consisted of three open-ended essay items developed based on the revised Bloom's Taxonomy cognitive levels, namely applying (C3), analysing (C4), and evaluating (C5) (Anderson & Krathwohl, 2001; Nafiati, 2021). The test blueprint is presented in Table 1.

Table 1. Test Blueprint of the Probability Learning Outcomes Test (with Example Item)

Item	Cognitive Level	Indicator	Example question (from the contextual scenario below)
1	C3 (Applying)	Determining relative frequency from indirectly given information	Determine how many oranges and bananas Gilang obtained in the first observation, then compute the relative frequency of oranges and bananas from his own records.
2	C4 (Analysing)	Comparing computed results with the expected probability and explaining the relationship	Compare the relative frequency of oranges from Gilang's own records with the combined class data, and analyse whether the friend's guess of 1 in 4 is supported.
3	C5 (Evaluating)	Evaluating which data set best approximates the true probability and justifying the choice	Decide which data set (personal or combined) better supports the provider's claim of a 15% chance of an orange, and give a logical justification.

The three items were built around a single contextual scenario, the "Free Nutritious Meal (MBG) fruit survey" problem: in a school meal programme, each package randomly includes either an orange or a banana. Over the first 20 days Gilang recorded that the number of oranges was six fewer than half of the observation days, and the remaining days yielded bananas. A classmate guessed that the chance of an orange was 1 in 4. To test the guess, Gilang surveyed 30 classmates on day 21 and merged their data with his own 20 records, giving 50 observations in total, of which only 8 were oranges. The meal provider, in turn, claimed a 15% chance of an orange. The three questions then ask students to compute the relative frequency (C3), compare it with the friend's guess (C4), and judge which data set best matches the provider's claim (C5).

Before being administered to the research participants, the test was reviewed by two expert lecturers in mathematics education to ensure face validity and content validity, and was then piloted with 30 tenth-grade (Grade X) senior high school students. Students one grade level above the research sample were deliberately chosen on the assumption that they had already completed the probability material, so that the trial could properly assess the quality of the items. The results of the expert validation are presented in Table 2.

Table 2. Expert Validation Results

Validator	Status	Area of Expertise	Aspects Assessed	Conclusion
V. A.	Lecturer, Mathematics Education	Inquiry and digital-based Realistic Mathematics	Face validity (clarity and correctness of language) and content validity (alignment with basic competencies and HOTS levels C3–C5)	Usable with minor revision
D. S.	Lecturer, Mathematics Education	Mathematical Problem Solving	Face validity and content validity (alignment with basic competencies and HOTS levels C3–C5)	Usable with minor revision

Following the validators' suggestions, minor revisions were made to the wording of the contextual items to remove potentially ambiguous phrases before the items were piloted. Both validators assessed each item on a dichotomous scale (face validity as yes or no; content validity as valid or not valid) and judged all three items valid on every criterion. The item-level Content Validity Index (I-CVI) and the scale-level average (S-CVI/Ave) were therefore both 1.00, and Lawshe's Content Validity Ratio was 1.00 for each item, showing full expert agreement on content relevance.

The validity of the achievement test items was analysed using the Pearson Product-Moment Correlation formula (Durasa et al., 2024). The pilot test involved 30 students, so that the critical value was determined with degrees of freedom $df = n - 2 = 28$ at a significance level of $\alpha = 0.05$, giving an r-table value of 0.361. An item was considered valid if r-count > r-table. The results are presented in Table 3.

Table 3. Validity of the Probability Learning Outcomes Test Items

Item	r-count	r-table (n = 30)	Decision
1	0.770	0.361	Valid
2	0.862	0.361	Valid
3	0.845	0.361	Valid

Since all coefficients exceeded the r-table value of 0.361, all items were declared valid and suitable for measuring students' mathematics learning outcomes on probability topics.

Reliability refers to the consistency of an instrument in producing stable measurement results (Sugiharni & Setiasih, 2018). Reliability was tested using Cronbach's Alpha. An instrument was considered reliable if the coefficient exceeded 0.60. The Cronbach's Alpha coefficient obtained was 0.757, which exceeds the minimum criterion of 0.60; the instrument therefore falls into the high-reliability category and can be considered reliable for measuring students' mathematics learning outcomes.

Procedures

The Deep Learning treatment was implemented over three meetings, each operationalising the three Deep Learning principles in probability tasks. First, Meeting 1:

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

"Relative Frequency Investigation Mission". Mindful learning: students consciously identified key information and observed the pattern of experimental results from a target-throwing activity. Meaningful learning: students connected relative frequency with a familiar game ("Target Hit"). Joyful learning: experiment- and game-based activities sustained students' enthusiasm. Second, Meeting 2: "Connecting Relative Frequency and Theoretical Probability". Students related empirical results to theoretical probability through guided investigation and discussion. The context was a "Mystery Box" game in which students drew snack prizes at random and compared the outcomes with the theoretical chances. Last, Meeting 3: "Expected Frequency". Students applied probability concepts to determine expected frequency in contextual situations and reflected on the reasonableness of their results. The context was a school canteen predicting how many portions of each menu item would sell.

Implementation of the Deep Learning Approach

To make the treatment transparent and replicable, this section describes how the approach was enacted. The Deep Learning approach was not a stand-alone method but was delivered through a five-phase Problem Based Learning (PBL) syntax, with the three principles embedded in each phase. This design mirrors the school's existing use of PBL while adding the depth that preliminary observations had found lacking. The syntax is summarised in Table 4.

Table 4. Implementation of the Problem Based Learning Syntax

No.	PBL Syntax	Description
1	Problem orientation	Students are given a contextual problem on relative frequency, theoretical probability, or expected frequency through a game.
2	Organising students to learn	Students form groups to discuss, pose questions, and plan an investigation.
3	Guiding individual or group investigation	Students run the experiment, collect data, and solve the problem with the researcher's guidance.
4	Developing and presenting work	Students process the experimental results and present their group's findings to the class.
5	Analysing and evaluating the problem-solving process	Students and the researcher reflect on the process and conclude the material studied.

The schedule and sub-topics are given in Table 5. The three teaching meetings took place on 7, 13, and 14 April 2026, and the posttest was administered on 5 May 2026.

Table 5. Research Activities and Mapping of the Deep Learning Principles

Meeting (Date)	Sub-topic	Mindful learning	Meaningful learning	Joyful learning
1 (7 Apr 2026)	Relative frequency	Consciously identifying key information and observing the pattern of target-throwing results	Linking relative frequency to the familiar "Target Hit" game	Experiment- and game-based activities sustaining enthusiasm
2 (13 Apr 2026)	Relative frequency and theoretical probability	Carefully comparing experimental results with theoretical chances and noticing randomness	Recognising that probability can predict everyday events	Bottle-flip and Mystery Box prize-drawing games
3 (14 Apr 2026)	Expected frequency	Deliberately selecting each possible outcome before computing expected frequency	Connecting expected frequency to canteen buying and selling	Active group discussion and presentation of results
4 (5 May 2026)	Posttest	n/a	n/a	n/a

After the three meetings, a posttest consisting of the three open-ended items was administered individually. A scoring rubric adapted from Vebrian et al. (2021) was used. Each student's total score (range 0–12) was converted to a 0–100 scale and classified into achievement categories following Isyana and Novitasari (2024).

Data Analysis

Data analysis was conducted using descriptive and inferential statistics with IBM SPSS Statistics 24. Descriptive statistics summarised students' achievement (number of students, maximum, minimum, mean, range, median, and standard deviation). A normality test (Shapiro–Wilk, $\alpha = 0.05$) was conducted because the sample was fewer than 50 students (Rinaldi et al., 2020). Hypothesis testing used a **one-tailed (left-sided) One-Sample t-Test** to check whether the class mean had reached the MMC of 80. The hypotheses were:

H_0: $\mu \geq 80$ (students' mathematics learning outcomes have reached the MMC)
H_1: $\mu < 80$ (students' mathematics learning outcomes have not reached the MMC)

Because SPSS reports a two-tailed significance value, the one-tailed significance was obtained by halving it. H_0 was rejected when the one-tailed significance was below 0.05 and the mean difference was negative, which together indicate a mean significantly below 80, To complement the significance test, a one-sample Cohen's d was computed as the mean difference divided by the standard deviation.

Research Findings

Mathematics learning achievement data were collected through a posttest administered after the three Deep Learning meetings. The test consisted of three open-ended probability items assessing the cognitive indicators applying (C3), analysing (C4), and evaluating (C5). The descriptive statistics are presented in Table 6. The class of 33 students obtained a mean of 73, a median of 75, a maximum of 92, and a minimum of 50, giving a range of 42 and a standard deviation of 11.80.

Table 6. Descriptive Statistics of Mathematics Learning Achievement

Statistic	Value
N	33
Mean	73
Median	75
Maximum	92
Minimum	50
Range	42
Standard deviation	11.80

The mean score of 73 falls within the moderate category. Based on the school's MMC of 80, 11 students (33.33%) reached the criterion while 22 students (66.67%) did not, indicating that most students had not yet reached the expected level of mastery in probability.

To show the shape of the distribution, Table 7 groups the scores into achievement intervals, and Figure 1 presents the same information as a histogram. No student scored below 41. Six students (18.18%) fell in the 41 to 60 interval, sixteen (48.48%) in the 61 to 80 interval, and eleven (33.33%) in the 81 to 100 interval, so that scores clustered in the middle band just below the mastery threshold.

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

Table 7. Distribution of Posttest Scores by Achievement Interval

Interval	Category	Number of students	Percentage
0–20	Not achieved (full remedial)	0	0%
21–40	Not achieved (major remedial)	0	0%
41–60	Nearly achieved (needs remedial)	6	18.18%
61–80	Achieved	16	48.48%
81–100	Achieved (needs enrichment)	11	33.33%

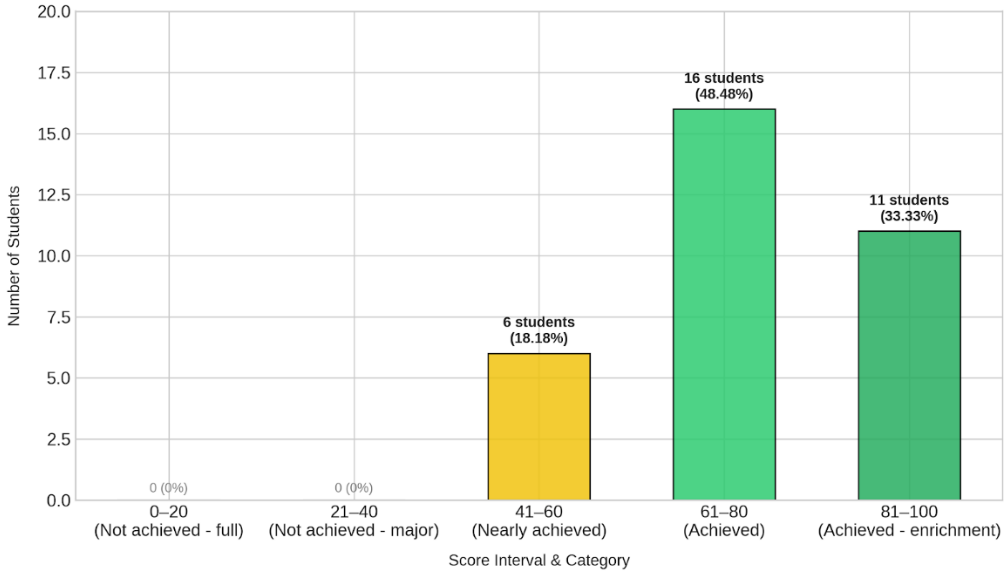

Figure 1. Histogram of posttest score distribution (frequency by interval).

An analysis by cognitive indicator clarified where students succeeded and where they struggled. On the C3 (applying) item, 26 of 33 students were able to use the probability formula and compute relative frequency correctly, especially when the information was stated directly. On the C4 (analysing) item, 20 students had difficulty selecting the correct strategy and linking the information in the problem to the appropriate probability concept. On the C5 (evaluating) item, 25 students struggled to check their answers or justify the reasoning behind their steps, often giving short conclusions without explanation. Achievement therefore declined as the cognitive demand rose from applying to analysing and evaluating.

The Shapiro–Wilk test yielded a statistic of W = 0.935 (which exceeds the critical value W-table = 0.931 for n = 33 at $\alpha = 0.05$) and a significance value of 0.058 (> 0.05); therefore H_0 was accepted and the posttest scores were normally distributed, as summarised in Table 8. Parametric testing (One-Sample t-Test) could thus be applied.

Table 8. Results of the Shapiro–Wilk Normality Test

df	Sig.	α	Decision
32	0.058	0.05	Normally distributed (H_0 accepted)

The result of the One-Sample t-Test is presented in Table 9.

Table 9. Results of the One-Sample t-Test (Test Value = 80)

t	df	Sig. (2-tailed, SPSS)	Sig. (1-tailed)	Mean Difference	Cohen's d
−3.408	32	0.002	0.001	−7.0 (negative)	−0.59

Because the test is one-tailed, the relevant significance value is Sig. (1-tailed) = 0.002 / 2 = 0.001 < 0.05, and the t-value of −3.408 together with the negative mean difference shows that the sample mean (73) is significantly **below** the test value of 80. The associated effect size

(Cohen's d = −0.59) indicates a medium-sized gap below the criterion. Therefore, H_0 is rejected in favour of H_1: students' mathematics learning outcomes on probability material, after the implementation of the Deep Learning approach, had not yet reached the MMC.

Discussion

The average student learning outcome in probability was 73 (highest 92, lowest 50), below the MMC of 80. This shows that, within the limited duration of implementation, the Deep Learning approach had not yet optimised students' conceptual understanding and higher-order thinking, particularly in analysis and evaluation tasks. An item-level inspection indicated that achievement was relatively adequate on the C3 (applying) item, where many students could determine relative frequency, but weakest on the C4 (analysing) and C5 (evaluating) items, where students struggled to compare empirical and theoretical probability, interpret contextual information, and justify their conclusions. The counts make this concrete: 26 students handled the C3 task, but 20 struggled with the C4 task and 25 with the C5 task. The difficulty therefore grew precisely where the reasoning demand grew, which is consistent with the documented tendency of students to confuse experimental data with theoretical expectation (Kazak & Pratt, 2021) and with the role of fragile proportional reasoning in probability (Begolli et al., 2021), since both C4 and C5 required students to interpret a relative frequency as a ratio and weigh it against a claim.

Several interrelated factors, observed during the learning process and recorded in the researcher's field notes, may explain this result. Classroom management during group discussions was less than optimal because the teacher-researcher supervised several groups simultaneously, so not all groups received equal scaffolding. The high density of activities in each meeting meant that much instructional time was spent on procedural implementation rather than deeper conceptual reflection. Differences in students' prior abilities, especially in basic operations such as division involving decimals, also contributed to difficulties. These observations are presented as field evidence rather than conclusive proof, given the design's limitations. The findings are consistent with Siregar et al. (2024), who relate low achievement to weak conceptual understanding and limited opportunities for critical thinking, and with Fitriana et al. (2026), who report that conceptual understanding develops only when instruction gives sustained attention to meaning rather than procedure.

The classroom process itself showed a gradual, uneven shift. In the first meeting, difficulty surfaced at the "organising students to learn" phase, where several students were not yet used to forming a conjecture or deciding what information to gather, and the decimal division involved in computing relative frequency drew attention away from interpreting the data. By the second meeting, engagement improved during the Mystery Box game, yet some students still could not clearly compare relative frequency with theoretical probability, and a few lacked the confidence to present. The third meeting showed the clearest progress: most students identified the key information in the canteen problem and began to connect probability with expected frequency, and discussion became more active. This trajectory suggests that the approach was beginning to work on engagement and meaning even though the posttest, taken soon after, did not yet capture a full shift in reasoning.

During the learning activities, particularly contextual experiments and collaborative problem-solving tasks, students appeared engaged and actively participated. The joyful learning principle was visible when students participated in probability simulations, while meaningful learning emerged as students connected empirical results with theoretical probability concepts. (No comparison with conventional classes is claimed, because the study did not include a control class.) By the final session, several students began to relate probability concepts to real-

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

life contexts such as canteen sales, suggesting that conceptual understanding had started to develop even though it was not yet fully reflected in posttest results. These observations align with Pujawati et al. (2025), who emphasise that Deep Learning focuses on conceptual depth rather than procedural mastery alone, and echo Rahmawati et al. (2026), who found that a joyful, student-centred design can lift reasoning-related outcomes even within a short window.

The findings are consistent with constructivist learning theory (Piaget and Vygotsky), which holds that knowledge is actively constructed through experience, social interaction, and reflection (Subiyantoro, 2025). Students constructed their understanding through experiments, discussions, and problem solving, but the development of analysis and evaluation skills required a longer adaptation process, as students were accustomed to teacher-centred, procedure-oriented learning. When compared with previous studies, the present results differ from Wahyudi (2025) and Marjiyem (2025); these differences are best explained by differences in research design (One-Shot Case Study without a comparison group versus comparative designs), treatment duration (only three meetings here), topic (abstract probability), and student characteristics, rather than by the superiority of any single approach. It is worth noting that the present mean of 73 sits slightly above the 72% conceptual-understanding figure reported by Marjiyem (2025), even though it falls short of the 81.6% posttest average reported by Wahyudi (2025); read together, these comparisons suggest a positive but not yet mastery-level effect under a short implementation. The findings suggest that time intensity, effective classroom management, and students' readiness to shift from procedural to conceptual learning are critical conditions for the Deep Learning approach to improve probability learning outcomes.

Implications of Findings

The first implication is pedagogical. Because achievement dropped sharply from the applying level to the analysing and evaluating levels, teachers who adopt a Deep Learning approach in probability should not assume that engagement alone will carry students to higher-order reasoning. The mindful and meaningful principles need explicit scaffolds at the C4 and C5 levels, for example structured prompts that ask students to state what a relative frequency means before they compare it with a theoretical value, so that the reasoning step is made visible rather than left implicit.

The second implication concerns assessment and the design of tasks. The single contextual scenario used here proved capable of separating the three cognitive levels, which is useful for diagnosis, but it also showed that students falter when a problem requires them to justify a choice between competing data sets. Assessment aligned with higher-order thinking, of the kind advocated by Bayu et al. (2026), should therefore include items that reward explanation and evaluation, not only correct computation, so that instruction and assessment pull in the same direction.

The third implication is about duration and scheduling. Three meetings were enough to lift engagement and to begin shifting students from procedure toward meaning, but not enough to consolidate analysis and evaluation, especially for students whose basic arithmetic was still fragile. Schools that wish to use this approach for abstract topics should plan for a longer sequence, with time reserved for reflection rather than filled entirely with activity, and with support for the prerequisite skills, such as working with ratios and decimals, that probability quietly depends on.

The fourth implication is for research. Because the One-Shot Case Study cannot isolate the effect of the approach, future studies should use pre-post or comparative designs, longer interventions, and richer process measures, including per-indicator growth and samples of student work, to trace how mindful, meaningful, and joyful learning translate into higher-order reasoning over time. Replication across other abstract topics and other school levels would help establish how far the present pattern generalises.

Conclusion

Based on the data analysis and hypothesis testing, students' mathematics learning outcomes on probability material after the implementation of the Deep Learning approach had not met the school's Minimum Mastery Criterion of 80. The one-sample t-test confirmed this: the class mean of 73 was significantly below 80 ($t = -3.408$, $p = 0.001$, one-tailed; Cohen's $d = -0.59$), with scores ranging from 50 to 92. At the indicator level, performance on C3 (applying) was relatively adequate, whereas many students still struggled with C4 (analysing) and C5 (evaluating), particularly in determining solution strategies, interpreting contextual information, and justifying answers. This study contributes evidence that, in an abstract topic such as probability, a Deep Learning approach delivered over a short duration may foster engagement and emerging conceptual understanding without yet producing mastery-level outcomes. Its limitations include the One-Shot Case Study design without a pretest or comparison class, a treatment duration of only three meetings, and a single-class sample of 33 students. Future research should employ a longer implementation, comparative or pre–post designs, and richer process measures to better evaluate the effectiveness of the Deep Learning approach.

Acknowledgement

The authors thank the principal, teachers, and Grade IX students of SMP Negeri 8 Tasikmalaya for their cooperation during the research, and the two validator lecturers for reviewing the instrument.

Conflict of Interest

The authors declare that there are no conflicts of interest.

Auhor Contributions

All authors confirm that they have read and approved the final version of this manuscript. F.A.R.P. conceptualised the study, designed and implemented the Deep Learning treatment, developed and administered the instrument, collected the data, and drafted the original manuscript. S.S. supervised the research, co-designed the methodology, validated the instrument, led the analysis and interpretation of the results, and substantially contributed to reviewing and editing the manuscript. N.R. supervised the research, validated the methodology and analysis, and contributed to reviewing and editing the manuscript. The percentage contributions for the conceptualisation, drafting, and revision of this paper are as follows: F.A.R.P.: 40%, N.R.: 20%, and S.S.: 40%.

Data Availability Statement

The authors state that the data supporting the findings of this study (students' posttest scores, instrument trial data, and validation sheets) will be made available by the corresponding author, S.S., upon reasonable request.

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

References

Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.

Anggraena, Y., Ginanto, D. E., Kesuma, A. T., & Setiyowati, D. (2025). *Panduan pembelajaran dan asesmen pendidikan anak usia dini, jenjang pendidikan dasar, dan jenjang pendidikan menengah* (Edisi Revisi 2025). Pusat Kurikulum dan Pembelajaran, Kemendikbudristek.

Bambang, M., Pajria, P., Amelia, R., & Apriliah, G. (2025). Pendekatan deep learning dalam meningkatkan kemampuan pemecahan masalah dan motivasi belajar siswa pada materi komposisi fungsi. *Pedagogy: Jurnal Pendidikan Matematika, 10*(4), 1519–1532. https://e-journal.my.id/pedagogy/article/view/7116

Bayu, B. R., Arvy, B. R., & Nasrullah, A. (2026). Enhancing high school students' critical thinking through HOTS-based interactive e-modules. *Kognitif: Jurnal Riset HOTS Pendidikan Matematika, 6*(1), 1–12. https://doi.org/10.51574/kognitif.v6i1.4492

Begolli, K. N., Dhillon, S., Devlin, B., Bagdasarov, A., & Richland, L. E. (2021). Could probability be out of proportion? Self-explanation and example-based practice help students with lower proportional reasoning skills learn probability. *Instructional Science, 49*, 685–711. https://doi.org/10.1007/s11251-021-09550-9

Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approaches* (6th ed.). SAGE.

Dewi, L. G. A. K., Hartawan, I. G. N. Y., & Astawa, I. W. P. (2019). Penerapan model eliciting activities (MEAs) berbantuan masalah open ended untuk meningkatkan pemahaman konsep matematika siswa. *Jurnal Pendidikan dan Pembelajaran Matematika Indonesia, 8*(2), 133–142. https://ejournal.undiksha.ac.id/index.php/JJPM/article/view/19986

Durasa, H., Mertasari, N. M. S., & Pujawan, I. G. N. (2024). Implementasi problem-based learning berdasarkan independensi belajar untuk meningkatkan kemampuan pemecahan masalah dengan mengontrol kecemasan matematis. *AKSIOMA: Jurnal Program Studi Pendidikan Matematika, 13*(2), 620–631. https://doi.org/10.24127/ajpm.v13i2.7102

Finariya, R., Susilaningtyas, T., & Mahmudah, M. (2023). Analisis kesulitan belajar matematika siswa kelas IX MTsS Nurul Islam Wuluhan pokok bahasan peluang di masa new normal tahun ajaran 2022/2023. *INDOPEDIA (Jurnal Inovasi Pembelajaran dan Pendidikan), 1*(4), 1476–1486. https://indopediajurnal.my.id/index.php/jurnal/article/view/216

Fitriana, T., Huda, N., & Syafmen, W. (2026). Effect of conceptual, understanding, procedural, and problem-based learning models using a contextual approach on students' conceptual understanding skills. *Kognitif: Jurnal Riset HOTS Pendidikan Matematika, 6*(1), 387–400. https://doi.org/10.51574/kognitif.v6i1.4433

García, T., Rodríguez, C., González-Castro, P., González-Pienda, J. A., & Torrance, M. (2016). How affective-motivational variables and approaches to learning predict mathematics achievement in upper elementary levels. *Learning and Individual Differences, 49*, 25–32. https://doi.org/10.1016/j.lindif.2016.05.021

Hammadi, S. S., Hamid, A. A., Jasim, R. K., & Kadhim, Q. K. (2023). Impact of deep learning strategy in mathematics achievement and practical intelligence among high school students. *International Journal of Emerging Technologies in Learning, 18*(6), 42–52. https://doi.org/10.3991/ijet.v18i06.38615

Isyana, B. V., Baidowi, Novitasari, D., & Sridana, N. (2024). Pengaruh self confidence terhadap hasil belajar matematika siswa kelas VIII SMP. *Mandalika Mathematics and*

Educations Journal, *6*(1), 370–383. https://jurnalfkip.unram.ac.id/index.php/MANDALIKA/article/view/7125

Juika, Dewi, S. V., & Heryani, Y. (2026). Effectiveness of problem-based learning with the teaching at the right level approach on students' mathematical concepts understanding ability. *Kognitif: Jurnal Riset HOTS Pendidikan Matematika, 6*(1), 216–226. https://doi.org/10.51574/kognitif.v6i1.3379

Kazak, S., & Pratt, D. (2021). Developing the role of modelling in the teaching and learning of probability. *Research in Mathematics Education, 23*(2), 113–133. https://doi.org/10.1080/14794802.2020.1802328

Marjiyem. (2025). Menggali makna konsep aljabar melalui deep learning: Penerapan operasi bentuk aljabar. *Jurnal Pendidikan Matematika, 5*(4). https://doi.org/10.17977/um068.v5.i4.2025.3

Nafiati, D. A. (2021). Revisi taksonomi Bloom: Kognitif, afektif, dan psikomotorik. *Humanika, 21*(2), 151–172. https://doi.org/10.21831/hum.v21i2.29252

Öçal, M. F. (2018). The case of time axis fallacy: 11th grade students' intuitively-based misconception in probability and teachers' corresponding practices. *Journal of Qualitative Research in Education, 6*(3), 1–20. https://doi.org/10.14689/issn.2148-2624.1.6c3s4m

Oktaviani, U., Kumawati, S., Apriliyani, M. N., Nugroho, H., & Susanti, E. (2020). Identifikasi faktor penyebab rendahnya hasil belajar matematika peserta didik di SMK Negeri 1 Tonjong. *MATH LOCUS, 1*(1), 1–6. https://doi.org/10.31002/mathlocus.v1i1.892

Peng, M. Y.-P., & Chen, C. C. (2019). The effect of instructor's learning modes on deep approach to student learning and learning outcomes. *Educational Sciences: Theory & Practice, 19*(3), 87–101. https://doi.org/10.12738/estp.2019.3.005

Pujawati, F., Rahayu, D. V., & Sritresna, T. (2025). Exploration of the implementation of deep learning approach in teaching mathematics in secondary schools. *Unnes Journal of Mathematics Education, 14*(2), 98–105. https://doi.org/10.15294/ujme.v14i2.27374

Rahmawati, S., Muzdalipah, I., & Muslim, S. R. (2026). Improving students' mathematical reasoning ability through the joyful learning model assisted by GeoGebra. *Kognitif: Jurnal Riset HOTS Pendidikan Matematika,* *6*(1), 33–43. https://doi.org/10.51574/kognitif.v6i1.1755

Riana, & Fitrianna, A. Y. (2021). Analisis kesulitan dalam menyelesaikan soal peluang pada siswa SMP kelas IX ditinjau dari taksonomi Bloom. *Jurnal Pembelajaran Matematika Inovatif, 4*(4), 1019–1032. https://doi.org/10.22460/jpmi.v4i4.1019-1032

Rinaldi, A., Novalia, & Syazali, M. (2020). *Statistika inferensial untuk ilmu sosial dan pendidikan*. IPB Press.

Silalahi, S. A., Zainal, A., & Sagala, G. H. (2022). The importance of deep learning on constructivism approach. In *Proceedings of the 2nd International Conference of Strategic Issues on Economics, Business and Education (ICoSIEBE 2021)* (pp. 243–246). Atlantis Press. https://doi.org/10.2991/aebmr.k.220104.036

Siregar, M. L., Winarni, S., & Marlina. (2024). Analisis kemampuan pemahaman konsep matematika model discovery learning pada siswa SMP. *Jurnal Pendidikan MIPA, 14*(1), 175–186. https://ejournal.tsb.ac.id/index.php/jpm/article/view/1503

Subiyantoro, S. (2025). *Problem and project-based learning*. Penerbit Lakeisha.

Sugiharni, G. A. D., & Setiasih, N. W. (2018). Validitas dan reliabilitas instrumen evaluasi blended learning matakuliah matematika diskrit di STIKOM Bali berbasis model Alkin. *IndoMath: Indonesia Mathematics Education,* *1*(2), 93–104. https://doi.org/10.30738/indomath.v1i2.2626

Kognitif: Jurnal Riset HOTS Pendidikan Matematika
https://doi.org/10.51574/kognitif.v6i3.5283 Volume 6, No 3, July - September 2026, pp. 1167 –1181

Sugiyono. (2023). *Metode penelitian kuantitatif, kualitatif, dan R&D*. Alfabeta.

Vebrian, R., Putra, Y. Y., Saraswati, S., & Wijaya, T. T. (2021). Kemampuan penalaran matematis siswa dalam menyelesaikan soal literasi matematika kontekstual. *AKSIOMA: Jurnal Program Studi Pendidikan Matematika, 10*(4), 2602–2614. https://doi.org/10.24127/ajpm.v10i4.4369

Wahyudi, D. A. (2025). Pengaruh pembelajaran deep learning terhadap kemampuan penalaran matematis dan kepercayaan diri siswa SMA Dharma Pancasila Medan. *Jurnal Inovasi Pendidikan PEDAGOGI, 1*(1), 9–17. https://sfa-alfatih-press.com/JIPP/article/view/26

Wijayanto, N. (2025). *Metode & strategi pembelajaran deep learning (pembelajaran mendalam)*. Mandita.

Authors Biography

	**Fitria Andyasti Rahayu Pranata** is student at Mathematics Education Study Program, Faculty of Teacher Training and Education, Universitas Siliwangi. ✉ pranatafitria7@gmail.com
	**Nani Ratnaningsih,** is a lecturer in the Mathematics Education Program, Faculty of Teacher Training and Education, Siliwangi University. The courses he teaches include Qualitative Research Methodology, Mathematics Education Seminar, Group Theory, Mathematics Education Research Methodology, Developmental Research Methodology, and Ring Theory. ✉ naniratnaningsih@unsil.ac.id
	**Satya Santika,** is a lecturer in the Mathematics Education Program at the Faculty of Teacher Education and Education, Siliwangi University. He teaches courses in algorithms and programming, educational multimedia, mobile learning, web-based learning, computer applications in mathematics, and information technology literacy. ✉ satyasantika@unsil.ac.id