Brain-Based Deep Learning Model Assisted by GeoGebra to Enhance Mathematical Problem-Solving Skills of Prospective Elementary School Teachers

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***Abstract*—This study aims to (1) develop a valid and practical Brain-Based Deep Learning model supported by GeoGebra for enhancing mathematical problem-solving skills; (2) examine its effectiveness in improving the performance of prospective elementary school teachers; and (3) evaluate its impact on self-efficacy and conceptual understanding. The research employed a Research and Development (R&D) design involving 250 students divided equally into experimental and control groups. Expert validation confirmed the model's high validity and practicality. The effectiveness test indicated a significant improvement in problem-solving skills for the experimental group compared to the control group. Qualitative analysis using NVivo identified five major themes: enhanced conceptual understanding, visualization experiences through GeoGebra, increased self-confidence, alternative strategy development, and collaborative reflection. These findings demonstrate that the developed model not only strengthens cognitive performance but also fosters affective growth, particularly in self-efficacy, offering a valuable contribution to innovative mathematics education for prospective teachers.**

***Keywords*—problem solving skills, brain-based learning, deep learning, GeoGebra, teacher education**

I. Introduction

The urgency of this research is driven by the challenges of improving the quality of mathematics learning and the importance of preparing elementary school teachers who are competent in mathematical problem solving. PISA 2022 data shows that Indonesian students' performance in the problem-solving domain is still below The Organisation for Economic Co-operation and Development (OECD) average, which calls for early educational intervention at the level of future teachers [1, 2]. Recent meta-analysis research reveals that Brain-Based Learning (BBL) approaches have a significant effect on students' conceptual understanding, with an effect size of ES = 3.135 in Science, Technology, Engineering, and Mathematics (STEM) subjects [3–6]. GeoGebra, as an interactive visual software, has also been proven to enhance students' mathematics achievement and learning engagement in quasi-experimental settings [7–10]. However, research combining BBL and GeoGebra in elementary teacher education remains limited. This combination is believed to be relevant because BBL leverages the principles of neuroplasticity and cognitive context to enhance critical thinking capacity, while GeoGebra provides a dynamic visualization medium that facilitates concrete understanding of abstract concepts [9, 11–13]. By integrating these two interventions, this study has the potential to develop a model for cultivating mathematical problem-solving skills that aligns with the cognition of prospective elementary school teachers, while addressing the need for systematic and sustainable improvements in the quality of mathematics education.

The main problem identified is the low mathematical problem-solving ability of prospective elementary school teachers, which has the potential to affect the quality of learning at the elementary level. Based on initial observations of 50 prospective elementary school teachers at STKIP Taman Siswa Bima in Bima Regency, West Nusa Tenggara Province (May 2025), the average score on a mathematical problem-solving test was only 62 out of 100, with 68% of participants scoring below the minimum competency standard. This data indicates a gap between academic competencies and teaching readiness. International studies also show that pre-service students are inadequately equipped with cognitive strategies such as visualization, problem decomposition, and metacognitive reflection [14–16], which are essential for high-standard mathematics instruction. This situation is exacerbated by the fact that only 24% of prospective teachers actively implement mathematical technology such as GeoGebra in their teaching [8, 13, 17]. Therefore, this study formulates the main problem: "How can a BBL-based training model combined with GeoGebra improve pre-service elementary school teachers' mathematical problem-solving skills?" The objectives of this study are to design and test the effectiveness of the model in improving test scores and problem-solving strategies, while also enhancing academic self-efficacy among pre-service teachers in teaching mathematics.

Initial observations were conducted through diagnostic tests and self-efficacy questionnaires on 50 prospective elementary school teachers in April 2025. Table 1 below shows the proportion of problem-solving performance categories:

Table 1. Proportion of problem-solving performance categories

Score Category	Number (n = 50)	Percentage
≥80 (High)	8	16 %
70–79 (Medium)	16	32 %
60–69 (Basic)	18	36 %
<60 (Low)	8	16 %

This data shows that only 16% of students are in the high category, while 52% are still in the basic and low categories. Descriptive analysis reveals an average score of 62 (SD = 8.7). The results of the self-efficacy questionnaire using a valid instrument show an average score of 3.1 (scale of 5), reflecting low confidence in overcoming mathematical problems. This data interpretation confirms that prospective teachers face motivational and cognitive strategy constraints, a situation that requires integrated coaching intervention. This situation is in line with previous findings that highlight the importance of BBL-based intervention to improve self-efficacy in mathematics [6, 18–21]. Therefore, the development of an integrated coaching model incorporating BBL and GeoGebra is expected to enhance the cognitive and affective skills of prospective teachers and serve as a contextual solution to the aforementioned issues.

In response to the low mathematical problem-solving abilities of prospective elementary school teachers, this study offers a solution in the form of a Brain-Based Deep Learning integrated coaching model supported by the use of GeoGebra as an interactive visual medium. Brain-Based Learning (BBL) is an educational approach rooted in neuroscience principles, focusing on activating the limbic system, frontal cortex, and brain reward system during learning [22–24]. When BBL is combined with the deep learning approach, learning not only touches the surface aspects (facts or procedures) but also stimulates deep, analytical, reflective, and metacognitive information processing [18, 25, 26]. The integration of this model is believed to overcome the limitations of conventional methods in developing higher-order thinking skills among prospective elementary school teachers. GeoGebra, as a visualization tool, also supports multisensory engagement in understanding mathematical concepts, which is highly compatible with BBL principles [27–30]. In this context, GeoGebra does not merely function as a technical tool but as a cognitive medium that accelerates the processing and integration of spatial, symbolic, and logical concepts. This study is designed to leverage the synergistic potential of both approaches to create a neurologically stimulating and pedagogically contextual learning environment focused on improving the quality of elementary education graduates. This training strategy is not only aimed at improving cognitive scores but also at transforming students' attitudes and academic self-confidence in teaching complex, problem-solving-based mathematics.

This research is presented in the current context that prioritizes neurocognitive-based learning innovation and educational technology as a response to the 5.0 education revolution. Various studies in the last three years have shown that the integration of BBL in primary and secondary education can improve concept retention, active participation, and critical thinking skills of students [31–34]. However, most of these studies have focused on school students rather than prospective teachers. Meanwhile, the development of 21st-century teacher skills, particularly in addressing numeracy and technology literacy challenges, requires specific interventions at the pre-service stage [35, 36]. Additionally, although GeoGebra has been extensively studied in the context of mathematics education, its integration into BBL-based training systems remains largely unexplored [37–39]. Therefore, this study builds on the state of the art at the intersection of brain-based learning theory, deep learning approaches, and interactive digital visualization. The developed model not only emphasizes content mastery but also on thinking strategies that activate balanced integration of the left and right brain, with technology serving as a cognitive mediator. This contributes to the development of a contextual learning model relevant to national and international standards in teacher education and expands the scope of neuroscience application in technology-based pedagogy.

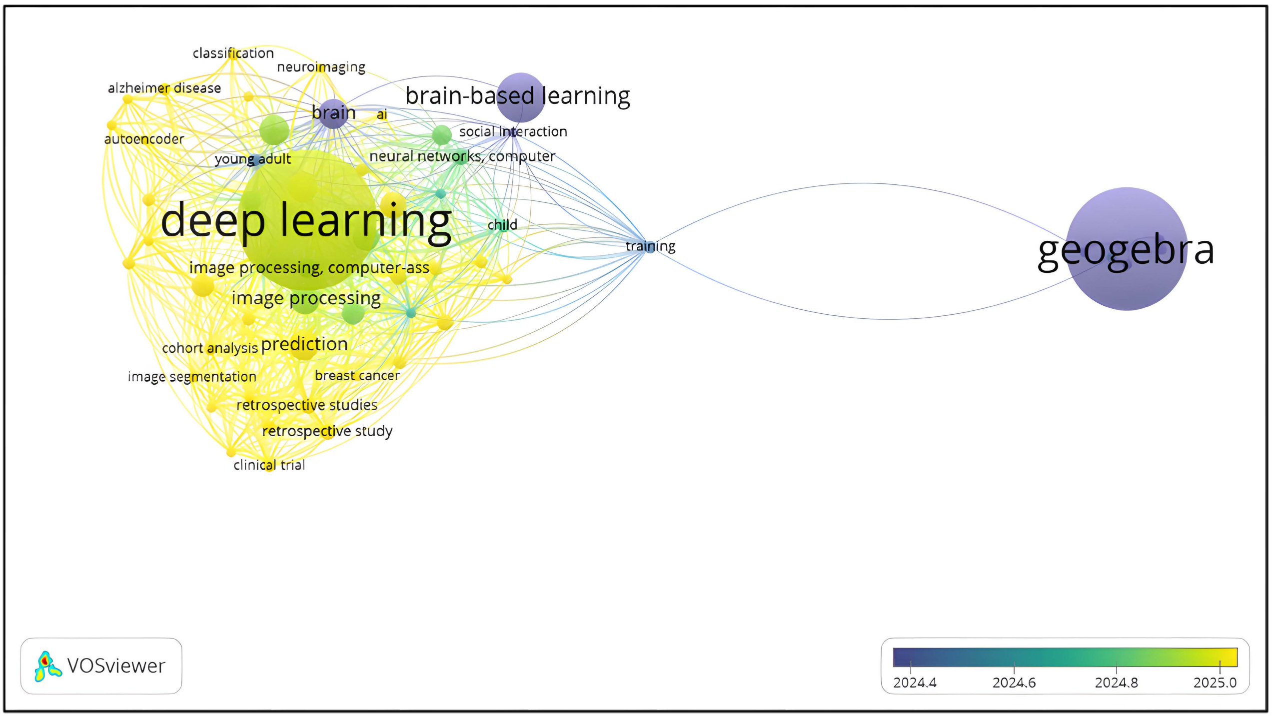

Fig. 1. Visualization of bibliometric mapping of brain-based learning, deep learning, and geogebra topics using VOSviewer.

The results of bibliometric mapping using VOSviewer in Fig. 1 show that the integration between brain-based learning, deep learning, and GeoGebra still forms a fragmented research ecosystem. The dominant cluster is centered on deep learning, which is strongly connected to topics in the fields of computing and medicine, such as image processing, prediction, and retrospective studies. Brain-based learning forms a minor node that is only connected to terms such as neural networks and child, without significant connections to visual learning technologies. GeoGebra nodes appear as large but isolated entities, indicating a lack of methodological integration with neuroscience and artificial intelligence approaches. Based on these gaps, this study offers a novelty in the form of a model for developing mathematical problem-solving skills that simultaneously combines brain-based neuroeducation principles, deep cognitive processing strategies, and the use of GeoGebra as a dynamic visual aid. This approach not only strengthens cognitive foundations but also addresses the affective domain, such as enhancing self-efficacy, making it a significant contribution to the literature on professional development for prospective elementary school teachers in the digital transformation era.

The innovation of this study lies in the systematic integration of Brain-Based Learning principles with a Deep Learning pedagogical framework and GeoGebra-assisted dynamic visualization within a single coaching model specifically designed for prospective elementary school teachers. Unlike prior studies that examine Brain-Based Learning, Deep Learning, or GeoGebra in isolation, this research proposes a unified neuro-pedagogical model that simultaneously targets cognitive depth, affective regulation (self-efficacy), and technological mediation in mathematical problem-solving. Furthermore, this study extends existing literature by validating the model through a mixed-methods approach that combines Rasch-based instrument validation, quasi-experimental effectiveness testing, PLS-SEM structural analysis, and qualitative thematic exploration, thereby offering a comprehensive and empirically grounded contribution to teacher education research.

Based on the background, empirical data, and state-of-the-art research described above, the research question proposed in this study is: "How effective is the Brain-Based Deep Learning and GeoGebra-based coaching model in improving the mathematical problem-solving skills of prospective elementary school teachers?" This formulation reflects a focus on pedagogical interventions aimed at simultaneously developing cognitive and affective abilities, supported by neuroscience-based learning strategies and digital mathematical visualization. The main objectives of this study are: (1) to develop a valid and practical Brain-Based Deep Learning and GeoGebra-based problem-solving skills training model; (2) to test the effectiveness of the model in improving the problem-solving skills of prospective elementary school teachers; and (3) to evaluate the impact of training on self-efficacy and mathematical conceptual understanding. This research utilizes an instructional design-based model development approach, with a series of expert validation, limited trials, and field trials. The objectives align with the strategic agenda for improving teacher education quality based on 21st-century competencies, particularly in the domains of numeracy and mastery of learning technologies. Therefore, the theoretical and practical contributions of this study are expected to strengthen the literature on teacher professional development and provide a scientific foundation for policies aimed at improving teacher education quality based on neuroscience and technology in Indonesia.

II. Materials and Methods

A. Research Types and Designs

This study uses a quantitative approach with a quasi-experimental design of the non-equivalent control group type, involving two groups: one experimental group and one control group. This design enables researchers to test the effect of a Brain-Based Deep Learning model assisted by GeoGebra on mathematical problem-solving skills by comparing the results before and after treatment between the two groups. The experimental group was given treatment using this model, while the control group received conventional learning that has been used in the regular curriculum.

This design was chosen based on field conditions where researchers could not fully randomize subjects but could ensure initial equality (pretest) between the two groups involved. This design has been widely used in educational research because it provides the power of causal analysis through direct comparison between two learning conditions [40–42]. The structure of this research design can be seen in Table 2 as follows:

Table 2. Research design

Group	Pre-test	Treatment	Post-test
Experiment	O_1	Brain-Based Deep Learning Model + GeoGebra	O_2
Control	O_1	Conventional Learning	O_2

The symbols O_1 and O_2 indicate the pretest and posttest used to measure mathematical problem-solving skills. Data from both groups will be analyzed statistically to see empirically significant differences.

B. Research Procedures

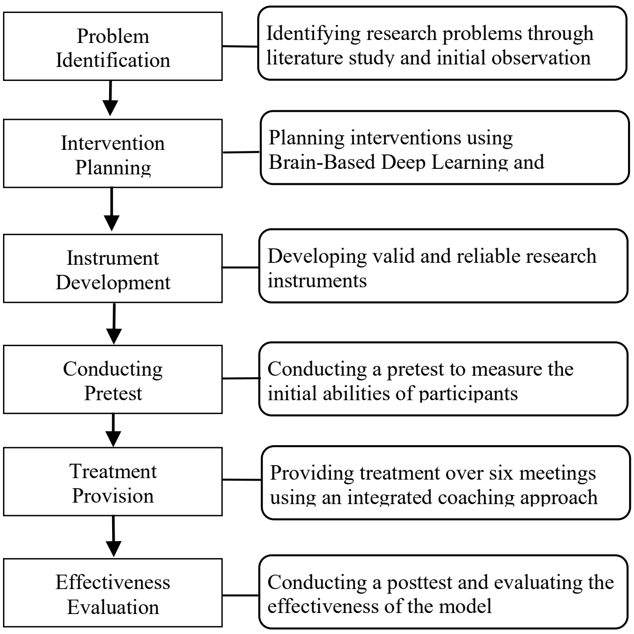

Fig. 2. Research procedure.

This research procedure was systematically and operationally organized into six main stages, as shown in Fig. 2. Each stage was designed sequentially to ensure the validity of the intervention process and the achievement of the research objectives, starting from problem identification to final evaluation, which describes the logical flow of the implementation of the GeoGebra-assisted Brain-Based Deep Learning coaching model. The research procedure was carried out in six systematic stages, namely.

C. Research Subjects or Participants

The participants in this study consisted of 250 prospective elementary school teachers from the Primary School Teacher Education (PGSD) program in their sixth semester. The subjects were selected using purposive sampling based on strict inclusion and exclusion criteria. Inclusion criteria included: active students, having completed the Basic Mathematics course, and willing to participate in the entire training process. Exclusion criteria were students who were not actively attending classes or had not completed the prerequisite courses.

Table 3. Classification of research participants

Category	Description
Total Number of Students	250 students
Experimental Class	125
Control Class	125
Gender (M/F)	110 Male / 140 Female
Semester	Semester VI
Study Program	Primary School Teacher Education (PGSD)
Inclusion Criteria	Active students who have completed the Basic Mathematics course and are willing to participate in the entire training process
Exclusion Criteria	Inactive students or those who have not completed the prerequisite course

The purposive sampling technique was applied to ensure that the selected participants accurately represented the population of pre-service elementary school teachers who met the pedagogical and cognitive readiness required for this study. This method allowed the researchers to focus on individuals with comparable academic backgrounds and learning experiences, ensuring the internal validity of the experimental design. In addition, Table 3 shows a total of 250 participants evenly distributed between the experimental group (n = 125) and the control group (n = 125) reflecting a fairly large and diverse sample that reflects the demographic composition of PGSD students at similar teacher education institutions in Indonesia. Therefore, this purposive selection provides not only relevance to the research objectives but also contextual representativeness for generalizing findings to the broader population of pre-service elementary school teachers.

D. Data Collection Techniques and Procedures

Data collection in this study was conducted through two main techniques: mathematical problem-solving ability tests and self-efficacy questionnaires. The tests were used to obtain quantitative data related to students' cognitive skills in solving context-based mathematical problems before and after the implementation of the coaching model. The self-efficacy questionnaire was used to measure students' academic confidence in their ability to teach and understand mathematical material. Data collection was carried out directly in the classroom using printed and digital formats, depending on the availability of student devices. Instrument validation was conducted through expert judgment by two mathematics lecturers and one learning media expert, using Aiken's V technique to test the suitability of the content, construct, and representation of indicators against the measurement objectives. In addition, readability was tested through a limited pilot test on five students outside the main subjects. The empirical validity of the instrument was strengthened through validity and reliability tests based on the Rasch Model using the Ministep application, while the structural validity of the questionnaire was tested through Exploratory Factor Analysis (EFA) with SmartPLS 4. Data were collected systematically in three stages: pretest in the first week, intervention for six weeks, and posttest in the eighth week. The entire process was conducted in accordance with research ethics principles, including informed consent and data confidentiality guarantees.

E. Data Collection Instruments

The main instrument in this study was a mathematical problem-solving skills test developed based on Bloom's revised cognitive taxonomy [43–45], covering the domains of analyze, evaluate, and create. The test consisted of six open-ended questions based on real-life contexts (realistic mathematical problems), compiled based on indicators of high mathematical thinking. Additionally, a self-efficacy questionnaire based on a 5-point Likert scale was used, consisting of 24 statements grouped into three dimensions: belief in teaching ability, confidence in solving mathematical problems, and willingness to explore mathematical technology. Tables 4 and 5 presents the instrument specifications:

Table 4. Test instruments (See Table A1)

Indicator Code	Indicator	Specific Description	Cognitive Domain	Number of Item
PM1	Identify relevant information	Filter important data from the context of the question	Analyze	4
PM2	Formulate a solution strategy	Select the appropriate mathematical procedure	Evaluate	4
PM3	Complete the mathematical procedure logically	Perform mathematical calculations correctly	Apply	4
PM4	Presenting solutions with mathematical reasoning	Explaining the reasons for the steps taken to solve the problem	Evaluate	4
PM5	Evaluate the results and check the accuracy of the solution	Check the results and correct any errors	Evaluate	4
PM6	Develop alternative solutions	Develop two different approaches to solve the problem	Create	4
Total				24

Table 5. Interview instrument

No	Interview Questions
1	How do you feel when you finish solving problems based on everyday life contexts?
2	How was your experience using GeoGebra in mathematics learning?
3	Did the learning approach help you understand mathematical concepts more deeply? Explain.
4	What was the biggest challenge you faced during the learning process with the Brain-Based Deep Learning model?
5	How did your perception of mathematics learning change before and after the treatment?
6	In your opinion, how does this learning approach relate to your problem-solving skills?
7	How would you rate your cognitive and emotional engagement during the learning process?
8	Do you feel more confident about teaching mathematics in the future after participating in this activity? Why?
9	Share your most memorable experience or moment during the learning process using GeoGebra.
10	What suggestions or recommendations would you like to offer for the future development of this type of learning?

F. Data Analysis Techniques

Data analysis was conducted using quantitative descriptive and inferential approaches. Instrument validity and reliability were examined using the Rasch model with MINISTEP, following established criteria proposed by Linacre and Bond and Fox. An item was considered to fit the Rasch model if its Infit MNSQ value ranged between 0.7 and 1.3, its Outfit ZSTD value fell within −2.0 to +2.0, and its Point Measure Correlation exceeded 0.30, indicating adequate alignment with the measured construct [46]. Items outside these thresholds were identified as underfitting or overfitting and were subject to revision. Subsequently, pretest and posttest data were analyzed using SPSS and JAMOVI, including normality, homogeneity, N-Gain, and hypothesis testing. Structural relationships involving self-efficacy were examined using SmartPLS, while qualitative data were analyzed through content analysis using NVivo to support interpretation of the quantitative results, can be seen in Table 6 as follows:

Table 6. Data analysis techniques

Type of Analysis	Techniques Used	Purpose of Analysis
Validity and Reliability of Instruments	Ministep Rasch Model	Items show strong validity and reliability results.
Normality Test	Kolmogorov-Smirnov	To test the distribution of data (α = 0.05)
Homogeneity Test	Levene Test	To check the similarity of variance between groups
Effectiveness Test	Calculating N-Gain Score (Hake: <0.3 low, 0.3–0.7 moderate, >0.7 high)	Determining the effectiveness of treatment on learning outcome improvement
Hypothesis Test	Paired sample t-test or Wilcoxon Signed Rank Test	Testing the difference between pretest and posttest results
Additional Analysis	Correlation between Self-Efficacy and Posttest using SmartPLS 4	To determine the mediating effect of perception on cognitive outcomes
Supporting Qualitative Analysis	Content Analysis using NVivo 12 Plus	To explore students' perceptions of the learning intervention

III. Result and Discussion

A. Validity and Reliability of Instruments (Ministep Rasch Model)

Quantitative analysis based on the Rasch Model using Ministep software produced a comprehensive mapping of item and respondent parameters, which are summarized in Table 7. This visualization presents the distribution of Infit Mean Square (IMNSQ), Outfit Mean Square (OMNSQ), Point Measure Correlation (PTMEASUR-AL), and the percentage of exact matches between responses and the measurement model. The presentation of this data serves as an empirical basis for assessing the validity and consistency of each item, while also identifying items that are fully consistent with the theoretical construct and those that require refinement.

The Rasch model analysis presented in Table 7 indicates that the test items demonstrate acceptable measurement quality based on established Rasch model criteria. Referring to Rasch measurement guidelines, Infit and Outfit Mean Square (MNSQ) values within the range of approximately 0.7–1.3 are considered indicative of good item fit, while standardized fit statistics (ZSTD) within −2.0 to +2.0 are generally regarded as acceptable for large samples. In this study, the majority of items fall within or close to these recommended ranges, indicating that students' response patterns are reasonably consistent with model expectations. Items with slightly elevated MNSQ values reflect mild underfit, suggesting greater response variability than predicted, whereas items with lower MNSQ values indicate overfit, meaning that responses were more predictable than expected. Importantly, such minor deviations do not threaten the overall measurement validity, as no items exhibit extreme misfit that would warrant removal. Furthermore, the positive point–measure correlations across items indicate that all items contribute meaningfully to distinguishing levels of mathematical problem-solving ability. Based on these quantitative criteria, the items can be interpreted as functioning adequately within the Rasch measurement framework. The observed variation in item difficulty reflects a deliberate design to capture a range of cognitive demands, supporting the instrument's purpose of assessing diverse aspects of mathematical problem-solving skills. Overall, the conclusions regarding item suitability are grounded in established Rasch fit criteria rather than subjective judgment, confirming that the instrument is appropriate for use in this study context.

Based on the summary statistics presented in Table 8, the quality of the measurement was evaluated using established Rasch model criteria. Specifically, the Infit and Outfit Mean Square (MNSQ) values fall within the acceptable range of 0.7–1.3, indicating a good model fit and confirming that both items and respondents function consistently within the Rasch measurement framework. In addition, the Outfit ZSTD values are within the tolerance range of −2.0 to +2.0, suggesting no substantial deviation between observed responses and model expectations. Within Rasch theory, MNSQ values exceeding the upper threshold indicate underfit, reflecting excessive randomness or noise in responses, whereas values below the lower threshold indicate overfit, where responses are overly predictable and contribute limited measurement information. At the item level, the high item reliability and large separation index quantitatively demonstrate the instrument's strong capacity to distinguish different levels of item difficulty in a stable and precise manner, supporting its structural coherence. In contrast, at the person level, the relatively low person reliability and separation indicate that participants' abilities were clustered within a narrow range, limiting discrimination among individuals; this outcome is more plausibly attributed to the homogeneity of the sample rather than deficiencies in the instrument itself. Therefore, the conclusion that the instrument "functions well" and is "appropriate" is grounded in explicit Rasch-based quantitative criteria and supported by established methodological standards, confirming the instrument's suitability for assessing mathematical problem-solving skills in the context of this study.

Table 7. Item fit statistics in Rasch model analysis

Entry number	Total score	Total count	Jmle measure	Model S.E.	Infit		Outfit		Ptmeasur-al		Exact match		Item
					MNSQ	ZSTD	MNSQ	ZSTD	CORR.	EXP.	OBS%	EXP%	
7	5760	75	–0.08	0.01	1.48	2.57	1.49	2.61	A	0.07	0.22	0	3.2
20	3721	75	–0.06	0.01	1.33	2.10	1.33	2.12	B	–0.21	0.30	1.3	2.4
22	3092	75	0.10	0.01	1.32	2.10	1.31	2.04	C	–0.17	0.29	2.7	2.3
24	2960	75	0.11	0.01	1.32	2.03	1.32	2.07	D	0.51	0.29	2.7	2.3
19	3710	75	–0.06	0.01	1.28	1.83	1.29	1.89	E	–0.30	0.30	4.0	2.5
1	6139	75	–0.12	0.01	1.26	1.43	1.28	1.54	F	0.15	0.20	1.3	3.7
10	4926	75	–0.01	0.01	1.22	1.31	1.24	1.43	G	–0.01	0.26	2.7	3.0
17	3656	75	0.07	0.01	1.21	1.41	1.20	1.37	H	0.26	0.30	0.0	2.5
13	4378	75	0.02	0.01	1.20	1.23	1.19	1.18	I	0.24	0.28	2.7	2.6
15	4416	75	0.02	0.01	1.18	1.13	1.19	1.17	J	0.00	0.28	0.0	2.7
21	2976	75	0.11	0.01	1.17	1.14	1.17	1.17	K	0.12	0.29	1.3	2.2
5	5568	75	–0.06	0.01	1.11	0.67	1.13	0.79	L	0.17	0.23	1.3	2.9
9	4993	75	–0.02	0.01	1.09	0.59	1.11	0.67	l	0.13	0.26	1.3	2.9
23	3119	75	0.10	0.01	1.11	0.76	1.10	0.72	k	0.38	0.29	2.7	2.2
11	4745	75	0.00	0.01	1.07	0.47	1.09	0.56	j	0.31	0.27	4.0	3.0
2	6099	75	–0.12	0.01	1.07	0.45	1.08	0.52	i	0.40	0.20	1.3	3.7
16	4322	75	0.03	0.01	1.06	0.44	1.06	0.42	h	0.24	0.28	2.7	2.6
3	6051	75	–0.11	0.01	1.04	0.28	1.04	0.31	g	–0.12	0.20	2.7	3.6
4	5888	75	–0.09	0.01	0.99	0.03	1.04	0.30	f	0.33	0.21	0.0	3.6
12	4987	75	–0.02	0.01	1.03	0.21	1.04	0.31	e	0.45	0.26	2.7	2.9
18	3828	75	–0.06	0.01	0.92	–0.54	0.91	–0.58	d	0.41	0.29	1.3	2.4
6	5453	75	–0.05	0.01	0.91	–0.52	0.90	–0.55	c	0.27	0.24	1.3	3.0
8	5499	75	–0.06	0.01	0.88	–0.72	0.89	–0.66	b	0.12	0.24	1.3	3.0
14	4467	75	0.02	0.01	0.73	–1.86	0.74	–1.77	a	0.39	0.28	1.3	2.7
MEAN	**4614.7**	**75.0**	**0.00**	**0.01**	**1.12**	**0.77**	**1.13**	**0.82**			**1.8**	**2.8**	
P.SD	**1033.8**	**0.0**	**0.07**	**0.00**	**0.17**	**1.02**	**0.17**	**1.01**			**1.1**	**0.5**	

Table 8. Summary statistics of Persons and items in Rasch model analysis

Category	Statistic	Total	75 Input		75 Measured		Infit		Outfit	
			Count	Measure	S.E.	Real S.E.	IMNSQ	ZSTD	OMNSQ	ZSTD
Person	Mean	1476.7	24	0.02	0.01	0.02	1.13	0.5	1.13	0.5
	P.SD	88.3	0	0.02	0	0	0.24	0.8	0.24	0.8
	Real RMSE			0.02						
	True SD			0.01						
	Separation						0.73			
	Person Reliability						0.35			
Category	**Statistic**	**Total**	**24 Input**		**24 Measured**		**Infit**		**Outfit**	
			Count	**Measure**	**S.E.**	**Real S.E.**	**IMNSQ**	**ZSTD**	**OMNSQ**	**ZSTD**
Item	Mean	4614.7	75	0	0.01	0.01	1.12	0.8	1.13	0.8
	P.SD	1033.8	0	0.07	0	0	0.17	1	0.17	1
	Real RMSE			0.01						
	True SD			0.07						
	Separation						7.84			
	Item Reliability						0.98			

Fig. 3 presents a Person–Item Map (Wright Map) that illustrates the alignment between the difficulty levels of the test items and the abilities of the participants on a common measurement scale. The map indicates that most participants are clustered around the middle range of the scale, suggesting relatively similar levels of mathematical problem-solving ability within the sample. Importantly, the majority of test items are also positioned around this central range, showing that the instrument is well matched to the overall ability level of the participants. Several items appear at the upper end of the map, indicating that they are more challenging and suitable for distinguishing participants with higher problem-solving abilities. Conversely, a smaller number of items are located at the lower end of the scale, functioning effectively to assess participants with more basic skills. This distribution demonstrates that the instrument covers a reasonable span of difficulty levels, allowing it to assess students across different levels of mathematical problem-solving competence. Overall, the Wright Map supports the conclusion that the test items are appropriately targeted to the participant group and that the instrument is capable of measuring variations in problem-solving ability without being overly easy or excessively difficult. This alignment reinforces the suitability of the instrument for evaluating mathematical problem-solving skills among prospective elementary school teachers within the context of this study.

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Fig. 3. Person-item map (wright map) in Rasch model analysis.

Table 9 summarizes respondents' measurement characteristics based on Rasch model analysis using established evaluation criteria. The mean Infit and Outfit Mean Square (MNSQ) values for persons are close to the ideal value of 1.0 and fall within the acceptable range of 0.7–1.3, indicating an adequate fit between respondents' response patterns and the measurement model. Likewise, the corresponding ZSTD values are largely within the tolerance interval of −2.0 to +2.0, suggesting no substantial misfit. In Rasch measurement theory, underfit (MNSQ > 1.3) reflects excessive randomness or inconsistent responding, whereas overfit (MNSQ < 0.7) indicates overly predictable responses that contribute limited diagnostic information. The observed statistics indicate that respondents generally interacted with the items in a manner consistent with the construct of mathematical problem-solving skills. However, the relatively low person reliability and separation indices quantitatively indicate limited dispersion in respondents' ability estimates, meaning that the instrument distinguishes only a small number of performance strata among participants. This restricted differentiation is more plausibly attributable to the homogeneity of the sample than to deficiencies in item functioning. Therefore, the conclusion that respondent data "fit the model" and that the instrument is "appropriate" is grounded in explicit Rasch-based quantitative thresholds, while also highlighting the need for more heterogeneous samples or a wider range of item difficulty in future studies to enhance person-level discrimination.

Table 9. Person summary statistics (S.E. of Person Mean = 0.00)

Item	Total Score	Count	Measure	S.E.	Infit		Outfit	
					MNSQ	ZSTD	MNSQ	ZSTD
Mean	1476.7	24	0.02	0.01	1.13	0.48	1.13	0.48
SEM	10.3	0	0	0	0.03	0.09	0.03	0.09
P.SD	88.3	0	0.02	0	0.24	0.81	0.24	0.81
S.SD	88.9	0	0.02	0	0.25	0.82	0.25	0.82
Max	1694	24	0.07	0.02	1.84	2.5	1.84	2.5
Min	1313	24	–0.01	0.01	0.48	–2.24	0.5	–2.13
Real RMSE	0.02	TRUE SD	0.01	SEPARATION	0.73	PERSON RELIABILITY		0.35
Model RMSE	0.01	TRUE SD	0.01	SEPARATION	0.9	PERSON RELIABILITY		0.45

Table 10 presents the item-level measurement properties based on Rasch model analysis using established quantitative criteria. The mean Infit and Outfit Mean Square (MNSQ) values are close to the ideal value of 1.0 and fall within the recommended acceptable range of 0.7–1.3, indicating that all items demonstrate a good fit to the Rasch measurement model. In addition, the corresponding ZSTD values generally remain within the tolerance interval of −2.0 to +2.0, suggesting no substantial misfit. In Rasch terminology, items with MNSQ values exceeding the upper threshold (>1.3) are classified as underfitting items, reflecting excessive noise or unpredictability, whereas items with values below the lower threshold (<0.7) are considered overfitting, indicating overly predictable responses that contribute limited new information. The observed item statistics indicate that neither problematic underfit nor excessive overfit is present in the instrument. Furthermore, the high item separation and reliability indices quantitatively confirm the instrument's strong capacity to distinguish multiple levels of item difficulty in a stable and precise manner. The range of item difficulty estimates demonstrates that the instrument adequately covers both lower- and higher-order problem-solving demands. Therefore, the conclusion that the items "function well" and are "appropriate" is grounded in explicit Rasch-based statistical thresholds and supported by authoritative measurement theory, providing clear evidence of strong internal validity and measurement stability for assessing mathematical problem-solving skills.

Table 10. Item statistics summary (S.E. of Person Mean = 0.02)

Item	Total score	Count	Measure	S.E.	Infit		Outfit	
					MNSQ	ZSTD	MNSQ	ZSTD
Mean	4614.7	75	0.00	0.01	1.12	0.77	1.13	0.82
SEM	215.6	0	0.02	0	0.03	0.21	0.03	0.21
P.SD	1033.8	0	0.07	0	0.17	1.02	0.17	1.01
S.SD	1056	0	0.07	0	0.17	1.04	0.17	1.03
Max	6139	75	0.11	0.01	1.84	2.57	1.49	2.61
Min	2960	75	−0.12	0.01	0.73	−1.86	0.74	−1.77
Real RMSE	0.01	TRUE SD	0.07	SEPARATION	7.84	PERSON RELIABILITY		0.98
Model RMSE	0.01	TRUE SD	0.07	SEPARATION	8.39	PERSON RELIABILITY		0.99

The content validation results confirm that the developed instrument and learning model possess strong content validity. Expert judgments indicated that all components—covering the alignment of indicators with theoretical constructs, the appropriateness of cognitive levels based on the revised Bloom's taxonomy, the relevance of contextual problem situations, and the clarity of language—were evaluated within the "highly valid" category. This finding signifies that the items and instructional elements adequately represent the domain of mathematical problem-solving skills intended to be measured, without conceptual distortion or construct underrepresentation. Minor revisions suggested by experts were limited to wording refinement and contextual clarity, rather than substantive changes to content or structure, indicating the robustness of the initial design. Consequently, the content assessment results provide empirical assurance that the instrument and model are theoretically grounded, systematically constructed, and suitable for subsequent stages of field testing and effectiveness evaluation, thereby strengthening the internal validity of the study and the credibility of its findings.

B. Statistical Assumption Testing (Normality and Homogeneity)

Based on the results of the normality test using the Kolmogorov-Smirnov method in Table 11 with a sample size of 125 participants in each group, the significance values (Sig.) obtained were 0.200 for the Control Pretest, 0.220 for the Control Posttest, 0.200 for the Experimental Pretest, and 0.227 for the Experimental Posttest. All significance values are above the threshold $\alpha = 0.05$, indicating that the data are normally distributed. This finding suggests that the distribution of scores in all measurement groups meets the normality assumption, thereby allowing the use of parametric statistical tests to appropriately assess differences and treatment effects in accordance with the research objectives.

Based on the results of the Levene's Test for homogeneity of variance in Table 12, the significance values (Sig.) for the four testing methods were obtained, namely Based on Mean at 0.952, Based on Median at 0.944, Based on Median and with adjusted df at 0.944, and Based on Trimmed Mean at 0.948. All significance values are greater than the $\alpha = 0.05$ threshold, indicating that the variances between groups in the entire dataset are homogeneous. This condition satisfies the assumption of homogeneity of variances, enabling the application of parametric analyses such as t-tests or ANOVA to appropriately test differences and treatment effects according to the study design.

Table 11. Results of Kolmogorov-Smirnov normality test

Class		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	*df*	Sig.	Statistic	*df*	Sig.
PM	Control Pretest	0.066	125	0.200*	0.992	125	0.734
	Control Posttest	0.087	125	0.220	0.974	125	0.018
	Experimental Pretest	0.058	125	0.200*	0.992	125	0.686
	Experimental Posttest	0.085	125	0.227	0.990	125	0.531

Note: * This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 12. Test of homogeneity of variance

Class		Levene Statistic	*df*1	*df*2	Sig.
PM	Based on Mean	0.114	3	496	0.952
	Based on Median	0.126	3	496	0.944
	Based on Median and with adjusted df	0.126	3	494.696	0.944
	Based on trimmed mean	0.121	3	496	0.948

C. Descriptive Analysis: N-Gain and Learning Effectiveness

Based on the results of the descriptive analysis in Table 13, there were consistent differences between the experimental and control groups in all problem-solving ability indicators (PM1–PM6) from the pretest to the posttest. The experimental group showed a higher average score increase on all indicators compared to the control group. For example, on indicator PM1, the average score increased from 10.26 to 13.32 in the experimental group, while the control group only increased from 9.86 to 11.43. A similar pattern was observed in indicator PM2, where the experimental group increased from 10.26 to 14.03, while the control group rose from 10.42 to 12.02. Indicators PM3 to PM6 also showed a significant upward trend in the experimental group, with relatively larger posttest mean differences compared to the control group. In addition, the relatively low standard deviation and variance in both groups indicate a homogeneous data distribution. The higher minimum and maximum value ranges in the experimental group in most indicators indicate that the model-based learning intervention used was able to encourage more optimal learning outcomes across a wider range of abilities. These findings overall reinforce that the treatment provided has a positive contribution to improving students' mathematical problem-solving abilities.

This quantitative improvement is further reinforced by qualitative evidence obtained from students' reflective responses during the learning process. Several participants reported that the use of GeoGebra helped them "understand the structure of the problem more clearly" and enabled them to "try different solution strategies without fear of making mistakes." Other reflections highlighted that the brain-based learning stages encouraged deeper thinking, particularly when students were required to explain their reasoning and evaluate the correctness of their solutions. These reflections align with the observed increases across indicators PM4 (reasoning), PM5 (evaluation), and PM6 (alternative strategies), indicating that the improvement in scores was not merely procedural but also reflected deeper cognitive engagement. The integration of these qualitative insights strengthens the interpretation of the descriptive results by demonstrating that the observed score gains correspond to meaningful changes in students' problem-solving processes and learning experiences.

Table 13. Description of research results

Measurement Variables	Group	*N*	Mean	Median	*SD*	Variance	Min.	Max.
PM1_Pretest	Experiment	125	10.26	10	0.943	0.889	8	12
	Control	125	9.86	10	1.006	1.011	7	13
PM1_Posttest	Experiment	125	13.32	13	0.989	0.977	11	16
	Control	125	11.43	11	1.145	1.312	9	14
PM2_Pretest	Experiment	125	10.26	10	1.062	1.127	8	13
	Control	125	10.42	10	0.977	0.955	8	13
PM2_Posttest	Experiment	125	14.03	14	1.092	1.193	12	17
	Control	125	12.02	12	1.020	1.040	10	15
PM3_Pretest	Experiment	125	10.23	10	1.283	1.647	7	13
	Control	125	10.06	10	1.396	1.947	7	13
PM3_Posttest	Experiment	125	13.53	13	1.089	1.187	11	17
	Control	125	11.30	11	1.150	1.323	9	14
PM4_Pretest	Experiment	125	11.19	11	1.045	1.092	9	14
	Control	125	11.25	11	1.068	1.140	9	14
PM4_Posttest	Experiment	125	14.80	15	1.114	1.242	12	17
	Control	125	12.77	13	1.093	1.196	11	15
PM5_Pretest	Experiment	125	10.72	11	1.140	1.300	7	14
	Control	125	10.66	11	1.178	1.389	8	13
PM5_Posttest	Experiment	125	14.14	14	1.098	1.205	11	17
	Control	125	11.56	12	1.139	1.297	9	15
PM6_Pretest	Experiment	125	9.77	10	1.144	1.309	7	13
	Control	125	9.67	10	1.120	1.254	7	12
PM6_Posttest	Experiment	125	13.30	13	1.172	1.375	10	17
	Control	125	11.56	12	1.117	1.248	9	14

Table 14. N-gain test results

Statistics	Experiment	Std. Error (Experiment)	Control	Std. Error (Control)
Mean	52.6708	1.39891	23.4482	1.48558
95% CI—Lower Bound	49.9019	-	20.5078	-
95% CI—Upper Bound	55.4396	-	26.3886	-
5% Trimmed Mean	53.2693	-	24.2753	-
Median	52.7778	-	24.3243	-
Variance	244.619	-	275.867	-
Std. Deviation	15.64029	-	16.60924	-
Minimum	0.00	-	−25.00	-
Maximum	90.70	-	54.55	-
Range	90.70	-	79.55	-
Interquartile Range	19.11	-	18.44	-
Skewness	−0.542	0.217	−0.720	0.217
Kurtosis	0.999	0.430	0.857	0.430

Based on Table 14, the N-Gain test results show that the average percentage increase in scores in the experimental group (Mean = 52.67; *SD* = 15.64) was in the moderate category and significantly higher than the control group (Mean = 23.45; *SD* = 16.61), which was in the low category. The 95% confidence interval for the experimental group is in the range of 49.90 to 55.44, while the control group is in the range of 20.51 to 26.39, which do not overlap, indicating a significant difference in improvement between the two groups. The median N-Gain of the experimental group (52.78) was also nearly twice as high as the median of the control group (24.32). The data distribution in the experimental group was relatively homogeneous with a score range of 0.00 to 90.70, while in the control group, the score range was from −25.00 to 54.55, indicating some decline in learning outcomes among some participants. The negative skewness values in both groups indicate a slight bias toward higher values, with positive kurtosis indicating that the distribution peaks are relatively sharper than in a normal distribution. Overall, these findings confirm that the learning model applied to the experimental group resulted in more substantial and consistent learning outcomes compared to the control group.

This quantitative evidence is corroborated by qualitative reflections from students in the experimental group, who reported experiencing clearer learning progression and greater confidence when solving mathematical problems. Several participants indicated that the structured stages of

Brain-Based Deep Learning, supported by GeoGebra visualization, enabled them to monitor their own improvement and recognize conceptual growth over time. Students also described that interactive visual feedback helped them identify errors and refine strategies, which aligns with the higher and more stable N-Gain distribution observed in the experimental group. These reflections strengthen the interpretation of the N-Gain results by showing that the measured learning gains correspond to authentic cognitive development rather than short-term score increases.

D. Hypothesis Testing

The results of the Independent Samples T-Test in Table 15 show that in the pretest stage, there were no significant differences between the experimental and control groups for all indicators PM1 to PM6 ($p > 0.05$), except for PM1_Pretest, which showed a significant difference ($t = 3.309$; $p = 0.001$). This indicates that the initial abilities of both groups were relatively equivalent on most indicators before the treatment was administered. Conversely, in the posttest stage, all indicators PM1 to PM6 showed significant differences with $p < 0.001$ and high t values (range $t = 12.039$ to 18.266), indicating that the experimental group achieved much higher learning outcomes than the control group. These findings provide strong evidence that the learning intervention implemented in the experimental group was effective in improving performance on all measured indicators.

Beyond statistical significance, these posttest differences reflect meaningful pedagogical effects of the Brain-Based Deep Learning model assisted by GeoGebra. Qualitative reflections from students in the experimental group revealed that the learning stages helped them better understand problem contexts, select appropriate strategies, and evaluate solution accuracy with greater confidence. Students also reported that dynamic visualizations facilitated deeper reasoning and supported alternative solution development, which aligns with the consistently higher posttest performance across PM1–PM6 indicators. Thus, the t-test results not only confirm the effectiveness of the intervention quantitatively but also correspond with observed improvements in students' cognitive engagement and strategic problem-solving processes.

Table 15. Independent samples t-test

Variables	Test Type	Statistic	*df*	*p*
PM1_Pretest	Student's t	3.309	248	0.001
PM1_Posttest	Student's t	13.951	248	<0.001
PM2_Pretest	Student's t	–1.240	248	0.216
PM2_Posttest	Student's t	15.026	248	<0.001
PM3_Pretest	Student's t	0.991	248	0.323
PM3_Posttest	Student's t	15.752	248	<0.001
PM4_Pretest	Student's t	–0.419	248	0.675
PM4_Posttest	Student's t	14.551	248	<0.001
PM5_Pretest	Student's t	0.436	248	0.663
PM5_Posttest	Student's t	18.266	248	<0.001
PM6_Pretest	Student's t	0.670	248	0.503
PM6_Posttest	Student's t	12.039	248	<0.001

Note. H_a $\mu_{Eksperimen} \neq \mu_{Kontrol}$

E. Correlation Test

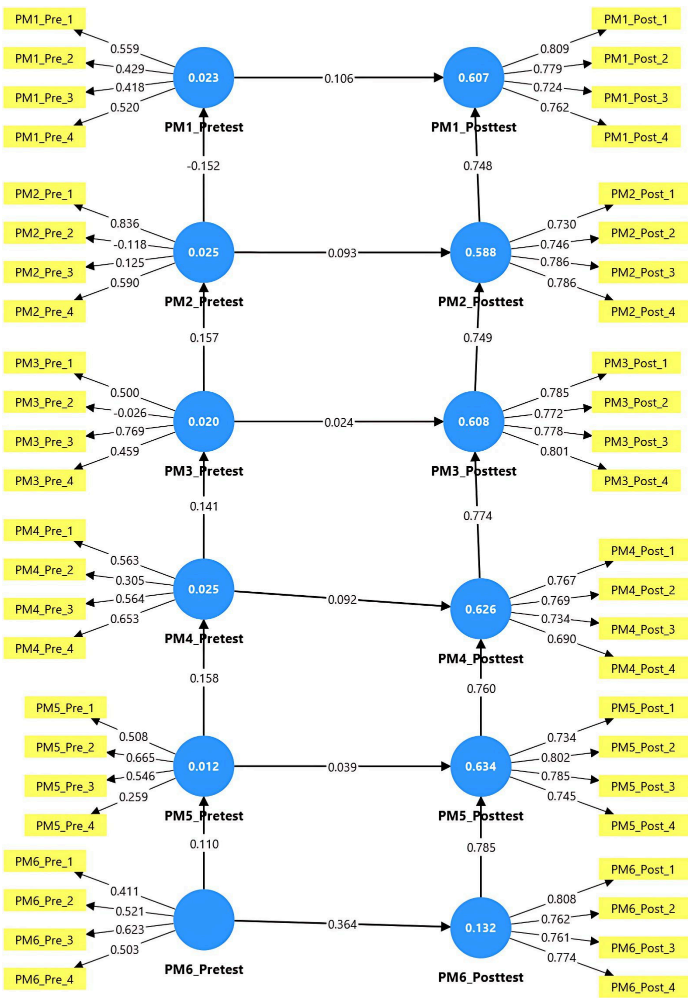

Fig. 4. Structural model and measurement (outer model and inner model) PLS-SEM analysis.

The results of Fig. 4 show the structural model and measurements (outer and inner models) in the PLS-SEM analysis that map the relationships between the observed indicators and latent constructs in each aspect of PM1 to PM6 in the pretest and posttest stages. In general, the outer loadings at the posttest stage show high consistency, with most indicators having values above 0.70, such as PM1_Post1 (0.809), PM5_Post2 (0.802), and PM3_Post3 (0.778), indicating very good indicator validity. Conversely, in the pretest phase, some indicators had loadings below 0.50, such as PM3_Pre2 (–0.026) and PM5_Pre4 (0.259), indicating that the indicators' contribution to the latent construct was still limited before the learning intervention. In the inner model, the path coefficients between the pretest and posttest constructs varied, such as PM1_Pretest → PM1_Posttest (0.106) and PM4_Pretest → PM4_Posttest (0.092), indicating a positive but relatively low influence, suggesting that posttest achievement was more influenced by the intervention than initial achievement. The R^2 values for the posttest constructs were moderate to high (0.588–0.634), while those for the pretest were very low (0.012–0.025), reinforcing that the variability in posttest results is more explained by the model built after the intervention. These findings confirm that the learning intervention has a significant impact on improving the validity of indicators and strengthening the relationship between constructs in all aspects of the measured abilities.

These results imply that the Brain-Based Deep Learning model assisted by GeoGebra played a decisive role in restructuring students' cognitive representations of mathematical problem solving. The substantial increase in posttest indicator validity and explained variance suggests that the intervention enabled students to internalize problem-solving processes more coherently, rather than merely relying on prior knowledge. From a pedagogical perspective, this indicates that the learning model effectively functioned as a cognitive scaffold, strengthening the alignment between observed behaviors and theoretical constructs across all problem-solving dimensions (PM1–PM6).

F. Qualitative Analysis of Interview Results

The results of the analysis of the code and theme connectivity map from the interviews in Fig. 5 show that all research participants contributed to various thematic categories that reflect cognitive, affective, and strategic dimensions in GeoGebra-based learning. The themes Improved Conceptual Understanding and Visualization Experience through GeoGebra became the center of connectivity, indicating that the use of interactive visual media played a significant role in deepening mathematical concept understanding and strengthening interconceptual connections [47, 48]. In addition, there was a strong connection to the theme Critical and Collaborative Reflection, which showed a process of deep reflection and collaborative discussion that encouraged participants to critically evaluate problem-solving strategies. The themes of Alternative Strategy Skills, Creative Approaches, and Multi-Step Solutions underscore improvements in flexibility of thinking and the ability to find various effective solutions. In the affective domain, Increased Self-Confidence and Positive Self-Perception reflect growth in self-confidence and positive perceptions of one's abilities, reinforced through active participation and the courage to express opinions. This overall connectivity pattern confirms that the implementation of a brain-based learning model supported by GeoGebra not only enhances academic competencies but also fosters critical thinking, collaboration, and independent learning skills.

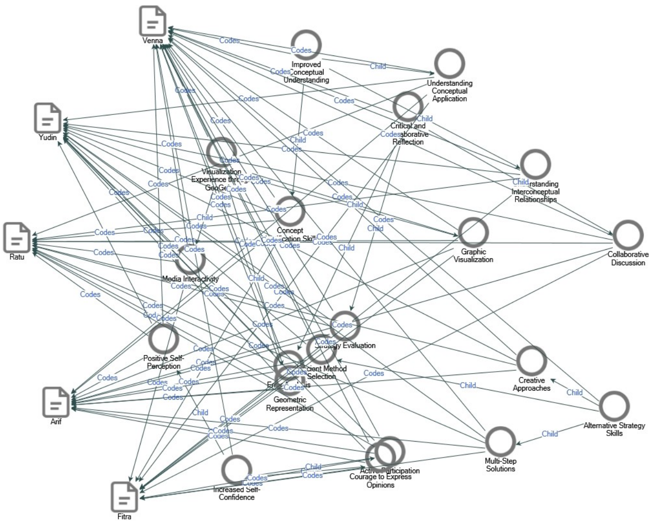

Fig. 5. Network visualization of codes.

G. Discussion

The results of the PM1 indicator show that there is a significant difference between the experimental and control classes in the posttest results, with a p-value of 0.001, which is less than $\alpha = 0.05$. The average posttest score for the experimental class was 13.32, while that for the control class was only 11.43. These findings indicate that the application of the GeoGebra-assisted Brain-Based Deep Learning model can improve students' ability to understand problems more deeply. From the NVivo qualitative analysis, the theme of increased conceptual understanding dominated the students' statements, which mentioned that interactive visualization helped them map information, identify important variables, and connect the problem context with relevant mathematical concepts. According to Tan *et al.* [49], the combination of verbal and visual representations can strengthen the understanding process by engaging dual cognitive pathways. In brain-based learning, the stimulation phase conducted through dynamic visualization in GeoGebra provides cognitive anchors that facilitate information processing. This effect is clearly evident in the higher N-Gain scores for PM1 indicators in the experimental group compared to the control group, indicating that students not only memorized information but also built strong mental models. Overall, these data reinforce the argument that good problem understanding is a crucial foundation for successful advanced problem-solving.

The PM2 indicator shows that the average posttest score for the experimental class was 14.03, significantly higher than that of the control class (12.02), with a p-value < 0.001. These findings confirm that brain-based learning utilizing GeoGebra can strengthen students' ability to plan appropriate solution strategies. Qualitative data from NVivo revealed that the theme of alternative strategy skills emerged consistently, indicating that students in the experimental class more frequently considered various strategy options before selecting a final solution. This aligns with the concept of cognitive flexibility [50–52] which states that exposure to diverse problem representations expands divergent thinking abilities. GeoGebra provides visual manipulation tools that allow students to predict the outcomes of an approach before executing it, making the chosen strategy more measurable and efficient. The Brain-Based Deep Learning approach, which emphasizes the integration of information from various areas of the brain, helps students connect previously separate mathematical concepts into a coherent strategic framework. The high N-Gain on this indicator shows that students did not simply repeat the same strategies but were able to adapt and develop new strategies according to the variations in the problems given.

On the PM3 indicator, the average posttest score for the experimental class was 13.53, while the control class scored only 11.30, with a p-value < 0.001. This difference indicates that the GeoGebra-assisted Brain-Based Deep Learning model is effective in improving students' skills in implementing planned solution strategies. Qualitative analysis results show a strong correlation with the theme of visualization experiences through GeoGebra, where students reported that interactive simulations made it easier to apply solution steps without losing the logical flow. Kolb's experiential learning theory explains that learning involving direct experience, such as manipulating mathematical objects digitally, can strengthen procedural skills while internalizing underlying concepts [53–55]. In this context, GeoGebra provides a quick and clear feedback loop, allowing students to immediately verify the steps they have taken. This process reduces procedural errors and improves calculation accuracy. N-Gain data on this indicator show consistent improvements in the experimental class, meaning that students are not only able to plan strategies but also execute them with a higher level of precision compared to the control group.

Indicators PM4 show that the average posttest score for the experimental class was 14.80, higher than that of the control class (12.77), with a p-value < 0.001. These results confirm that the use of GeoGebra within the Brain-Based Deep Learning framework strengthens students' ability to check their answers. Student reflection data analyzed using NVivo linked this achievement to the themes of critical and collaborative reflection. Students stated that the dynamic linking feature in GeoGebra facilitated the verification process because every change in input directly affected the visual and numerical representations. This facilitates Brain-Based Learning, which emphasizes the involvement of the prefrontal cortex in decision-making and evaluation of results [56, 57]. The ability to review results is a crucial metacognitive skill in advanced problem-solving. In the experimental class, this skill developed more rapidly because students were engaged in structured group discussions where calculation results were collectively verified. The combination of self-check and peer review strengthened the validity of solutions and reduced the likelihood of undetected errors.

The average posttest score for indicator PM5 in the experimental class was 14.14, far above the control class, which only reached 11.56, with a p-value < 0.001. These results indicate that the application of the GeoGebra-assisted Brain-Based Deep Learning model not only improves problem-solving abilities but also strengthens mathematical communication skills. From the NVivo coding results, the theme of increased self-confidence emerged as a key factor influencing students' success in presenting solutions clearly and structurally. This self-confidence was built through repeated successes in visualizing concepts and receiving positive feedback from the learning environment. According to Vygotsky's social constructivism theory, social interaction supported by visual aids can enrich the process of constructing mathematical arguments [58–60]. GeoGebra serves as a supporting medium that facilitates students in explaining mathematical procedures and reasons behind the solutions provided, both verbally and in writing. This improvement indicates that communication skills are not merely linguistic abilities but also the result of strong conceptual understanding and high self-confidence.

The PM6 indicator recorded an average posttest score of 13.30 for the experimental class, higher than the control class at 11.56, with a p-value < 0.001. The ability to generalize concepts and apply them to new contexts is a characteristic of high-level meaningful learning. Qualitative data from NVivo indicate that themes related to improved conceptual understanding and alternative strategy skills significantly contributed to the success of this indicator. With the assistance of GeoGebra, students were able to explore problem variations and examine how parameter changes affect outcomes, thereby strengthening their knowledge transfer skills. Within the Brain-Based Deep Learning framework, these skills are closely related to the activation of brain areas responsible for pattern recognition and cognitive adaptation [56, 61]. The significant N-Gain results on this indicator indicate that experimental class students not only understood the taught material but also applied it to new situations with high success rates. This proves that the integration of brain-based learning strategies and interactive visual technology is effective in building sustainable higher-order thinking skills.

IV. Conclusion

This study successfully developed a Brain-Based Deep Learning-based problem-solving skill training model supported by GeoGebra, which has high validity and practicality. The development process followed a systematic procedure, involving expert validation of content, construct, and language aspects, resulting in validity scores in the "highly valid" category. The practicality of the model was demonstrated through limited trials and field trials, where lecturers and students provided positive feedback on the clarity of learning steps, ease of implementation, and the alignment of materials with the learning objectives of mathematics in the elementary school teacher education program. This model integrates brain-based learning principles, such as multi-sensory stimulation, reinforcement of concept connections, and the use of interactive visual media to strengthen long-term memory. GeoGebra serves as the primary medium for visualizing abstract concepts into concrete and dynamic representations, thereby enhancing students' active engagement. As a result, the developed model is not only theoretically sound but also effectively implementable in a classroom setting to cultivate problem-solving skills among prospective elementary school teachers.

The effectiveness test showed that the Brain-Based Deep Learning and GeoGebra-based coaching model had a significant effect on improving the problem-solving skills of prospective elementary school teachers. The Independent Samples T-Test results for all problem-solving skill indicators (PM1–PM6) showed significant differences in posttest scores between the experimental class and the control class, with p-values < 0.001 in almost all indicators. The average N-Gain value in the experimental class reached the "moderate–high" category, consistently higher than the control class, indicating that students in the experimental group experienced greater improvement in understanding problems, planning strategies, implementing procedures, checking results, communicating solutions, and generalizing concepts to new situations. The integration of GeoGebra facilitates interactive visualization and real-time feedback, which accelerates the process of verifying and improving solution strategies. These findings are consistent with cognitive neuroscience theory, which states that the simultaneous activation of visual and verbal pathways can accelerate information processing and strengthen concept retention. Thus, this model has proven effective in fostering comprehensive problem-solving skills.

The evaluation of the impact of this coaching model shows a significant improvement in the aspects of self-efficacy and mathematical conceptual understanding of prospective elementary school teachers. Qualitative analysis based on NVivo reveals that the themes of increased self-confidence, deeper conceptual understanding, and alternative strategy skills emerged dominantly in the reflections of students in the experimental class. Students reported that repeated success in solving problems through GeoGebra visualization increased their confidence in their ability to face complex mathematical challenges. In addition, structured brain-based learning in this model facilitated inter-conceptual connections, enabling students to build more coherent mental models, thereby facilitating the application of concepts in new contexts. These impacts are not only cognitive but also affective, directly supporting students' readiness to become teachers capable of teaching mathematics creatively and effectively. Thus, this training model has strong potential to be adopted as a sustainable learning strategy in elementary school teacher education.

Despite its strong empirical support, this study has several limitations that should be acknowledged to contextualize its findings. First, the research was conducted within a single institution, which may limit the generalizability of the results to broader contexts of teacher education in Indonesia. Second, the intervention period was relatively short, focusing primarily on one semester of implementation, which may not fully capture the long-term retention of problem-solving and self-efficacy improvements. Future research should expand the model's implementation across multiple institutions and longer durations to examine its sustainability and adaptability in varied educational settings. Additionally, comparative studies involving in-service teachers or the integration of other emerging technologies—such as augmented reality or artificial intelligence-based learning tools—would provide valuable insights into how Brain-Based Deep Learning models can evolve to meet diverse pedagogical needs. Such extensions would not only strengthen the external validity of this model but also enrich its theoretical framework within the broader discourse of neuroscience-informed digital pedagogy.

APPENDIX

A. Mathematical Problem-Solving Test Instrument

Table A1. Test instruments

Indicator Code	Indicator	Cognitive Domain (Revised Bloom)	Item No.	Situational Test Question
PM1	Identifying relevant information	Analyze	1	Dina bought 3 books at Rp15,000 each and 2 pencils, with a total cost of Rp60,000. What information is relevant to determine the price of one pencil?
			2	Roni traveled 120 km in 3 hours. What information is needed to calculate the average speed?
			3	A mother bought 5 liters of cooking oil and 3 kg of rice for Rp130,000. Identify the information required to determine the price per liter of cooking oil.
			4	A bus departed at 6:30 a.m. and arrived at 9:00 a.m. What information is required to calculate the travel duration?
PM2	Formulating a solution strategy	Evaluate	5	In a competition, scores are calculated using the formula (S = 2x + 3y). What strategy should be used to calculate the final score?
			6	Solve the equation (3x + 2 = 11). What strategy can be used to find the value of x?
			7	Two consecutive even numbers have a sum of 34. What strategy can be applied to solve this problem?
			8	A store offers a 20% discount for purchases over Rp100,000. What is the most efficient strategy to calculate the final price?
PM3	Executing mathematical procedures	Apply	9	Solve the equation (2x − 4 = 10).
			10	If the side length of a square is 15 cm, calculate its area.
			11	A car travels 180 km at a speed of 60 km/h. Calculate the travel time.
			12	The price of one apple is Rp3,500. What is the total price for 8 apples?
PM4	Presenting solutions with reasoning	Evaluate	13	Given (5x − 7 = 18), explain each step used to solve the equation and justify the reasoning.
			14	Calculate the area of a triangle with a base of 10 cm and height of 6 cm, and explain the process.
			15	Explain why ((3 + 4) \times 2 \neq 3 + (4 \times 2)).
			16	Why is it important to use consistent units when measuring distance and time?
PM5	Evaluating and verifying results	Evaluate	17	After solving (5x + 2 = 27), a student obtained (x = 5). Verify whether the answer is correct.
			18	A student claims that 25% of 200 is 30. Is this correct? Explain your reasoning.
			19	Recalculate the area of a rectangle with a length of 8 cm and width of 3 cm.
			20	Someone states that (6 \times 7 = 36). Is this correct? Provide the correct answer and explanation.

PM6	Developing alternative solutions	Create	21	Provide two different methods to solve (3 \times 12).
			22	Determine two different strategies to calculate the area of a circle with a radius of 7 cm.
			23	Solve a purchasing problem using two approaches: (a) direct discount and (b) unit price comparison.
			24	Provide two different solution methods to solve (45 \div 3).

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest, whether financial, personal, or professional, that could influence the objectivity and integrity of the results of this study. This study was conducted independently, without the involvement of parties with political, religious, ideological, academic, or intellectual interests that could potentially influence the process and results of the study.

AUTHOR CONTRIBUTIONS

A.A.A. conceptualized the study, designed the research framework, conducted the research, and prepared the original draft of the manuscript. A. contributed to the development of the research methodology, supervised the data collection process, and assisted in reviewing and editing the manuscript. A.F. performed the statistical analysis, interpreted the research data, and contributed to critically revising the manuscript for important intellectual content. All authors discussed the results and approved the final version of the manuscript.

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