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AI-supported neuroeducational methodologies and logical-mathematical thinking in teacher training

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Abstract

The study examined the effect of neuroeducational methodologies supported by artificial intelligence on logical-mathematical thinking in teachers in training in Basic General Education at the Technical University of Ambato, Ecuador. A quantitative approach was used with a quasi-experimental, longitudinal pre-test-posttest design with non-equivalent groups. The sample was made up of 480 students, distributed in a control group that received mathematics teaching supported by conventional ICT and an experimental group that participated in a 14-week intervention based on neuroeducational methodologies supported by artificial intelligence. Data were collected through a 21-item performance test that evaluated logical-relational reasoning, abstraction and mathematical representation, and strategic problem solving. The internal consistency of the instrument was adequate (Cronbach's alpha = 0.816; McDonald's omega = 0.817). The analysis included descriptive statistics, ANCOVA, and linear regression in Jamovi. After controlling for pre-test scores, the ANCOVA showed a significant effect of group on post-test logical-mathematical thinking $F(1,477) = 206$, $p < 0.001$, $\eta^2p = 0.302$. Linear regression indicated that belonging to the experimental group significantly predicted final performance ($B= 0.810$, $\beta= 0.882$, $t= 49.0$, $p < 0.001$). The results suggest that neurodidactic methodologies structured and supported by artificial intelligence can strengthen logical-mathematical thinking in initial teacher training.

Keywords:
Artificial intelligence, Logical-mathematical thinking, Neuroeducational methodologies, Teacher training

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1. INTRODUCTION

In higher education, mathematics teaching has begun to shift from models focused on repetition to proposals that seek to develop reasoning, abstraction, and problem-solving in technology-mediated contexts. Within this scenario, artificial intelligence (AI) has gained presence as a support resource to personalize learning, offer feedback, and accompany processes where reflection is applied during the resolution of mathematical tasks. For this reason, recent evidence shows favourable results from different educational contexts, especially when AI is integrated into pedagogical proposals with metacognitive support and well-structured didactic sequences (Junpeng, 2026; Liu et al., 2026; Yi et al., 2025).

In addition, in teacher training, positive experiences with chatbots, virtual assistants, generative environments that support planning, problem statement, and reflective practice of future teachers have been documented (Jeong & González-Gómez, 2025; Kim et al., 2026; Zhang et al., 2025). This trend is very relevant because logical-mathematical thinking does not depend only on the mastery of procedures, but also on processes of abstraction, mathematical sense and conceptual construction.

Logical-mathematical thinking in pre-service teachers represents a critical component of educational quality because future teachers are not only expected to solve mathematical tasks, but also to guide reasoning processes, promote conceptual understanding, and facilitate problem-solving in school contexts (Mafarja et al., 2026). Weak development of logical-mathematical thinking during initial teacher education may later affect instructional quality, the selection of pedagogical strategies, and the ability to foster analytical reasoning among school students. Consequently, strengthening these competencies during teacher preparation has implications that extend beyond individual academic performance and directly influence the quality of mathematics education delivered in basic education systems.

In this context, neuroeducational methodologies acquire particular relevance because they integrate principles associated with executive functions, attention regulation, working memory, cognitive flexibility, and metacognitive monitoring into the learning process (Birtwistle et al., 2025). In mathematics education, these principles are reflected through activities oriented toward pattern recognition, strategic reasoning, error analysis, multiple representation, and reflective problem solving. Therefore, the integration of artificial intelligence into neuroeducational environments is pedagogically meaningful when AI-based tools support adaptive feedback, scaffolded learning, and self-regulated reasoning processes rather than merely automating instructional tasks (Banihashem et al., 2025).

From a theoretical perspective, the study is situated at the convergence of cognitive, neurodidactic, and pedagogical approaches to technological integration. The theory of cognitive development allows us to understand that the construction of logical-mathematical thinking requires a progressive reorganization of schemas and levels of abstraction (Piaget, 1977). Added to this is the idea of relational understanding in mathematics, according to which learning implies establishing connections between concepts, procedures, and meanings rather than merely reproducing mechanical responses (Skemp, 1978). Likewise, the literature on mathematical abstraction has insisted that formal reasoning is constructed through processes of representation, generalization, and reorganization of knowledge (Scheiner, 2016).

The contributions of recent studies to the field of neurodidactics allow us to affirm that working memory, attentional control and other components of executive functions greatly influence learning and performance (Espinoza-Ortiz & Guerrero-Jiménez, 2026; Ji & Guo, 2023; Ruffini et al., 2024). Consequently, on this basis, AI acquires pedagogical interest when it acts as a mediator of learning, error monitoring and task adaptation (Rui et al., 2025; Wu et al., 2025); that is, not only as an automation tool.

On a level closer to the Latin American educational field and initial teacher training, the discussion no longer revolves only around access to technology, but also to the pedagogical quality of their integration. Thus, recent reviews have shown that AI can support mathematical learning, teachers' technological literacy and didactic planning. However, its effectiveness depends on the institutional context, teacher preparation, and the pedagogical purpose guiding its incorporation into classroom practice (Kohnke et al., 2025; Panqueban & Huincahue, 2024).

Likewise, in teacher training, benefits associated with self-efficacy, instructional differentiation, class design and guided virtual practice have been identified. But, there are also limitations related to operational dependence, the ethics of the use of AI and curricular integration (Bond et al., 2025; Tegero & Mabini, 2025; Zagami, 2024; Ziying et al., 2026). In this sense, current studies offer a promising outlook; although still heterogeneous. This leaves open the need for studies aimed at examining concrete results in populations, especially of future teachers.

About the Ecuadorian case and particularly in the training of teachers in Basic General Education, this need is still visible. In the documentary corpus reviewed for this research, no studies were identified specifically focused on the Technical University of Ambato (UTA). No studies were identified that analyze the effect of neuro-educational methodologies supported by artificial intelligence on the logical-mathematical thinking of teachers in training. Likewise, the evidence reviewed does not offer works directly equivalent to the context, population and methodological combination proposed in this study. For this reason, this absence matters because if the integration of AI continues to occur without rigorous evaluation, without an explicit neuro-didactic framework and without contextual evidence. The teaching of mathematics can continue to rely on digital resources of low cognitive level with apparent but unsustainable improvements. This limitation in teacher training has a cumulative effect. In other words, future teachers with little preparation to reason mathematically and to incorporate AI with pedagogical criteria will tend to reproduce weak practices in the school classroom.

This context contributes to the broader discussion by showing how an AI-supported neuroeducational intervention can be implemented in a Latin American public university with heterogeneous academic trajectories and different levels of technological familiarity. Therefore, the study extends current evidence beyond highly digitalised educational systems and offers situated guidance for curriculum innovation in mathematics teacher education.

In view of the above, this study was guided by the following question: To what extent does the application of neuro-educational methodologies supported by artificial intelligence influence the logical-mathematical thinking of teachers in training in Basic General Education (EGB), compared to a teaching of mathematics supported only by conventional ICT? In accordance with this question, the objective was to determine the effect of neuro-educational methodologies supported by artificial intelligence on the logical-mathematical thinking of teachers in training in Basic General Education. To meet the objective, the following hypotheses were formulated:

Hypothesis 1

H_{11} Alternative: By controlling for pre-test scores, pre-service teachers who participate in neuro-educational methodologies supported by artificial intelligence obtain significantly higher post-test scores in logical-mathematical thinking than those who receive teaching supported only by conventional ICT.

H_{10} Null : Controlling for pre-test scores, there are no significant differences in post-test scores in logical-mathematical thinking between pre-service teachers who participate in neuro-educational methodologies supported by artificial intelligence and those who receive teaching supported only by conventional ICT.

Hypothesis 2

H_{21} Alternative: Participation in neuro-educational methodologies supported by artificial intelligence significantly predicts the final performance in logical-mathematical thinking of teachers in Basic General Education training.

H_{20} Null : Participation in neuro-educational methodologies supported by artificial intelligence does not significantly predict the final performance in logical-mathematical thinking of teachers in Basic General Education training.

2. METHOD

The research was developed from a quantitative approach, with a quasi-experimental, longitudinal pre-test-posttest design with non-equivalent groups (Basterra-González et al., 2026). The scope was explanatory and inferential, aimed at estimating the effect of the intervention based on neuro-educational methodologies supported by AI on logical-mathematical thinking (Ferrari et al., 2026).

2.1. Context and Participants

The study was conducted at the Technical University of Ambato, Ecuador, with students enrolled in the Basic General Education programme of the Faculty of Human Sciences and Education. The programme had an accessible population of 502 students distributed from the first to the eighth academic cycle. Therefore, the 480 participants did not represent the entire institutional population, but a selected sample that met the inclusion criteria established for the study. Participants were pre-service teachers enrolled in regular academic cycles, with an age range between 18 and 28 years. Purposive sampling was applied, considering current enrolment, minimum attendance of 85%, full participation in the intervention process, and availability of complete pre-test and post-test data (Ibrahim et al., 2026). Students who did not meet these criteria were excluded from the final database. Each academic cycle had two parallel classes, A and B, and each parallel was adjusted to 30 students. Consequently, the final sample consisted of 480 students: 240 in the control group and 240 in the experimental group. Parallel A received mathematics teaching supported by conventional ICT, whereas Parallel B participated in the AI-supported neuroeducational intervention.

2.2. Technique and Instrument

The data collection technique was the application of a performance test. The Evaluation of Logical-Mathematical Thinking in Higher Education was designed as an instrument, consisting of 21 items distributed in three dimensions: logical-rational reasoning, abstraction and mathematical representation, and strategic problem solving. Each dimension was made up of seven items with a combination of multiple-choice questions and short answers (see Table 1).

Table 1. Structure of the pretest-posttest instrument for assessing logical-mathematical thinking

Variable	Dimension	Key indicators	Items	Item Type	Scoring
Logical-mathematical thinking	Logical-relational reasoning	Patterns, seriation, classification, deduction and logical inference	1–7	Closed and open	0–1 / 0–2
Logical-mathematical thinking	Abstraction and mathematical representation	Symbolic translation, interpretation of tables and graphs, modelling and generalisation	8–14	Closed and open	0–1 / 0–2
Logical-mathematical thinking	Strategic problem solving	Strategy selection, sequencing, verification, error detection and justification	15–21	Closed and open	0–1 / 0–2

The instrument was applied in pre-test and post-test format with equivalent structure and its technical quality was supported by expert judgement and internal consistency analysis. The instrument was specifically designed for this study based on the theoretical dimensions associated with logical-mathematical thinking identified in the specialised literature on mathematical reasoning, abstraction, and strategic problem solving (Asempapa & Lee, 2025; Kania et al., 2024). The construction process included the operational definition of dimensions, indicator specification, item development, and alignment with the objectives of initial teacher education in mathematics. Subsequently, the instrument underwent content validation through expert judgement conducted by specialists in mathematics education, educational research, and assessment design (Henríquez-Rivas & Vergara-Gómez, 2025; Santágueda-Villanueva et al., 2025). The experts evaluated clarity, coherence, relevance, and correspondence between items and dimensions. After this process, minor wording adjustments were incorporated before the pilot application.

To make the structure of the instrument more transparent, representative examples of the assessed tasks were included. In the logical-relational reasoning dimension, items required students to identify numerical or visual patterns, complete sequences, classify information, and justify logical inferences. In the abstraction and mathematical representation dimension, students interpreted tables, graphs, and symbolic expressions, and translated contextual situations into mathematical representations. In the strategic problem-solving dimension, items asked students to select appropriate procedures, detect errors in a proposed solution, and justify the sequence of steps used to solve a mathematical problem.

2.3. Data Collection Instrument Reliability Analysis

To verify the consistency of the data collection instrument, a pilot test was applied to 53 students. The reliability of the instrument was estimated using Cronbach's alpha and McDonald's omega. The results showed values of 0.816 and 0.817 (see Table 2). This indicates an adequate internal consistency of the scale for its application in the study (Madadizadeh & Bahariniya, 2025).

Table 2. Internal consistency of the logical-mathematical thinking instrument

	Cronbach's Alpha	McDonald's ω
scale	0.816	0.817

2.4. Procedure

In the first week, the baseline diagnosis phase was developed. The purpose was to determine the initial level of logical-mathematical thinking of the participants. To this end, a diagnostic evaluation was conducted using the pre-test as the primary assessment technique. The diagnostic test and attendance record were used as a support resource with the support of Google Forms. The data were recorded in an Excel file. The learning outcome was to establish the performance baseline for subsequent comparison.

During weeks 2 and 3, the neuro-didactic induction phase of artificial intelligence was developed, aimed at introducing the pedagogical use of AI and its relationship with the self-regulation of mathematical learning. In this stage, the guided modeling method was applied. This was accompanied by techniques such as demonstration, assisted practice and the analysis of examples. The resources used included the initial guide, the teaching presentation and the participation rubric. The activities were supported by ChatGPT, Notebook in virtual classroom and Canva software. The student recognized the academic and ethical use of AI as a support for mathematical reasoning.

In weeks 4 and 5, the phase of logical reasoning and pattern recognition was executed, whose purpose was to develop the identification of relationships, sequences, and regularities in mathematical problems. This phase was based on the problem-based learning method and was worked on through guided solving, collaborative work and strategy contrast. The support resources were exercise guides, worksheets and logical sequences with the use of ChatGPT, GeoGebra and Quizizz. Participants analyzed patterns and selected solution procedures with greater logical consistency.

In weeks 6 and 7, the abstraction and representation phase was developed aimed at strengthening mathematical abstraction and translation between verbal, graphic and symbolic representations. To do this, the comprehension method was used with modeling, commented explanation and multiple representation techniques. The resources included graphic organizers, contextualized exercises, workbook with the support of GeoGebra, Canva and ChatGPT. In this phase, the student represented mathematical relationships with greater conceptual and argumentative precision.

During weeks 8 and 9, the strategic resolution phase was applied, with the purpose of consolidating heuristic strategies for problem solving and error control. This stage was developed using the heuristic method, employing techniques such as case studies, selfevaluation, and feedback. The supporting resources were the problem bank, the checklist and the error diary with the use of ChatGPT and GeoGebra. The students projected problem solving with greater precision and correction of procedural errors in an argumentative way.

In weeks 10 and 11, the transfer phase to EGB was developed, aimed at applying logical-mathematical thinking to didactic situations. In this phase, we worked with the situated learning method, through micro-planning techniques, task adaptation and peer review. The resources used were the planning format, the EGB curriculum and the didactic rubric with the support of ChatGPT, Canva and PowerPoint. The students designed mathematical activities relevant to educational contexts.

In weeks 12 and 13, the integration and autonomy phase was developed, the purpose of which was to integrate the learning acquired and strengthen cognitive autonomy with support from AI. To this end, the method of supervised reflective practice was used, accompanied by techniques such as independent resolution, co-evaluation and brief tutoring. The support resources used included the integrative guide, the portfolio, complex problems with the use of ChatGPT, and the virtual classroom. At this stage, the student solved problems with greater autonomy, justifying decisions with a critical evaluation in support of the AI.

In week 14, the final evaluation phase was developed, the purpose of which was to assess the effect of the intervention on logical-mathematical thinking. The summative evaluation method was applied, using post-test techniques and contrast of results. The resources used were the final test, the comparative sheet and the database, all this with the support of Google Forms and Excel. The result was to show the final level of performance for comparison with the baseline and with the control group.

2.5. Analysis Technique

For the statistical analysis of the results, the Jamovi software version 2.7.23 was applied (Pagano et al., 2025). Descriptive statistics were calculated to summarize the behavior of the variables studied, through the calculation of measures of central tendency and dispersion. Subsequently, the necessary assumptions for the inferential analysis, the normality of the residuals, the homogeneity of variance, the homogeneity of slopes and linearity were verified.

To test the main hypothesis, a covariance analysis (ANCOVA) was used, considering the post-test as a dependent variable, the group as a fixed factor and the pre-test as a covariate (Hruby, 2026). In addition, linear regression was applied in order to examine the predictive value of the intervention on the final performance in logical-mathematical thinking (Huang et al., 2024).

2.6. Ethics

Participation was voluntary, under confidentiality and anonymous coding of the data in accordance with the ethical principles applicable to educational research. The collection instrument was analyzed and validated by the research ethics committee of the UTA, under the resolution of the semester research project in education.

3. RESULTS AND DISCUSSION

3.1. Results

Before the inferential analysis, the assumptions of residual normality, variance homogeneity, slope homogeneity and linearity were verified. There was no evidence of serious violations that would prevent the application of ANCOVA and linear regression.

3.1.1. Descriptive statistics of the pre-test and post-test according to group

In the initial mediation, both groups showed equivalent means in logical-mathematical thinking (Control: M = 10.8, SD = 5.41; Experimental: M = 10.8, SD = 5.53), indicating comparable starting conditions. In the post-test, both groups registered improvements; however, the increase was greater in the experimental group (Control: M = 13.1, SD = 5.11; Experimental: M = 15.7, SD = 4.53) (see Table 3).

Table 3. Descriptive statistics for pretest and posttest score by group

Statistic	Group	Pretest	Posttest
N	Control	240	240
	Experimental	240	240
M	Control	10.8	13.1
	Experimental	10.8	15.7
SD	Control	5.41	5.11
	Experimental	5.48	4.53

3.1.2. ANCOVA results of the post-test in logical-mathematical thinking

A covariance analysis was performed to examine the effect of the intervention on logical-mathematical thinking in the posttest, controlling for pre-test scores. As noted, the group effect was statistically significant $F(1,477) = 206$, $p < 0.001$, $\eta^2p = 0.302$. Likewise, the pretest was maintained as a significant covariate $F(1, 477) = 2401$, $p < 0.001$, $\eta^2p = 0.834$ (see Table 4). These results indicate that after adjusting for baseline differences, students in the experimental group obtained significantly higher post-test scores than those in the control group.

Table 4. ANCOVA results for posttest logical-mathematical thinking scores

Source	SC	df	MC	F	P	η^2p
Group	799	1	798.61	206	<.001	0.302
Pretest	9307	1	9307.15	2401	<.001	0.834
Residual	1848	477	3.88	---	---	---

3.1.3. Estimated marginal means of the post-test according to group

The estimated marginal means allowed us to specify the adjusted differences between the groups in the post-test. The experimental group achieved a higher adjusted measure (M= 15.7, EE= 0.127; 95% CI [15.5, 16.0]) compared to the control group (M= 13.1, EE= 0.127; 95% CI [12.9, 13.4]) (see Table 5 and Figure 1). This pattern confirms the advantage of the experimental group once the initial performance has been controlled.

Table 5. Estimated marginal means for posttest logical-mathematical thinking scores by group

Group	Adjusted Average	EE	95% lower CI	95% upper CI
Control	13.1	0.127	12.9	13.4
Experimental	15.7	0.127	15.5	16.0

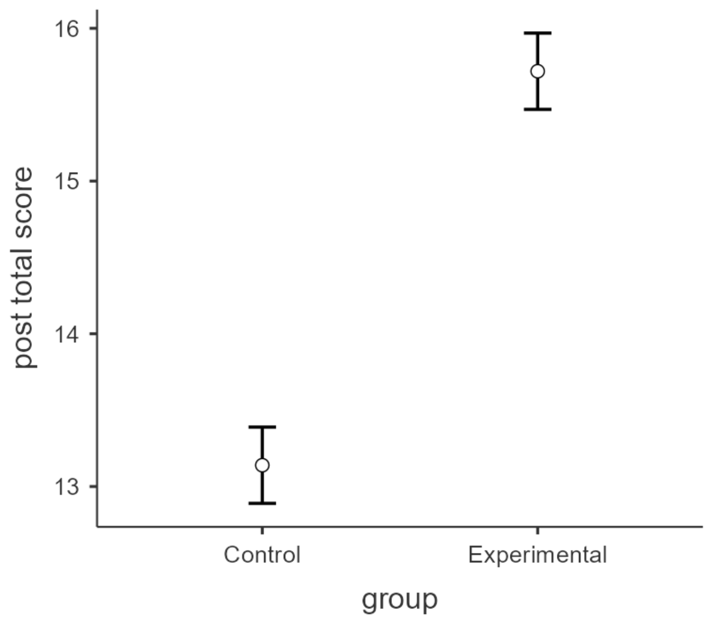

Figure 1. Estimated marginal means of posttest logical-mathematical thinking scores by group

3.1.4. Results of the linear regression of final performance in logical-mathematical thinking

Linear regression was applied to determine whether baseline performance and group membership predicted final performance in logical-mathematical thinking. The model was statistically significant and explained 84.5% of the post-test variance (R2 = .845). The pretest score was a positive and significant predictor of final performance (B= 0.810, β= 0.882, t= 49.0, p < 0.001) (see Table 6). Membership of the experimental group compared to the control group was also a significant predictor of post-test (B=2.580, β= 0.516, t= 14.4, p < 0.001). These results indicate that in addition to initial performance, participation in neuroeducational methodologies supported by artificial intelligence significantly predicted the final performance of students.

Table 6. Linear regression model predicting posttest performance in logical-mathematical thinking

Predictor	B	EE	t	p	b	95% CI
Constant	4.393	0.219	20.1	< 0.001	---	---
Pretest (pre total score)	0.810	0.017	49.0	< 0.001	0.882	[0.847, 0.917]
Group (Experimental vs Control)	2.580	0.180	14.4	< 0.001	0.516	[0.444, 0.587]

Note: Dependent variable: total post-test score in logical-mathematical thinking.
Model fit: R= 0.919; R2 = 0.845

3.2. Discussion

The findings of the study show that neuroeducational methodologies supported by artificial intelligence were associated with better performance in logical-mathematical thinking in teachers in training in Basic General Education. Although both groups started from comparable initial conditions in the pretest, the experimental group achieved a higher final performance in the posttest. This difference was maintained even after statistically controlling for baseline score using ANCOVA. The pattern coincides with recent studies that have reported favorable effects of artificial intelligence when integrated into pedagogical proposals with metacognitive scaffolding, immediate feedback and structured didactic sequences. In addition, it is emphasized that there are improvements in mathematical learning through intelligent tutors and with neurodidactic proposals that are oriented to cognitive development in school contexts (Alvarez, 2024; Zhumabayeva et al., 2025). Likewise, the results are consistent with studies that have indicated that the development of logical-mathematical thinking is related to academic performance in the population of teachers in training (Shirawia et al., 2023).

From an interpretive perspective, the observed difference between groups suggests that the pedagogical value of artificial intelligence does not lie in its mere presence. Rather, it lies in the way it is articulated with didactic decisions aimed at reasoning, representation, and strategic problem solving (Badolo et al., 2025; Flores & Peña, 2024; Prabawanto, 2019). In other words, the better performance of the experimental group should not be read as an automatic effect of technology. This should be interpreted as the result of pedagogical mediation that organised mathematical work through intelligent tools, self-regulation guidelines, and timely feedback. This reading is also supported by research that has highlighted the role of metacognitive scaffolding in AI learning environments and by studies that have underlined the need to integrate these tools into explicit pedagogical frameworks for teacher training (Rui et al., 2025; Wu et al., 2025; Zhang & Zhang, 2026).

The ANCOVA provided a relevant result, since it showed that the difference in favor of the experimental group did not depend only on the initial performance. In educational studies with intact groups and without individual randomization, this methodological aspect was decisive. In fact, the methodological literature included in the supporting corpus indicated that ANCOVA was an appropriate strategy for pre-test and post-test designs with non-equivalent groups. All this, because it allowed adjusting for baseline differences and improving the validity of inference in natural classroom contexts (Andrade, 2021; de Oliveira Almeida, 2026; Dugard & Todman, 1995; Karabinus, 1983). The use of this analysis strengthened the interpretation of the effect of the intervention and reduced the risk of attributing post-test changes to previous inequalities between groups.

The results of the linear regression complemented this reading, as the pretest emerged as a strong predictor of final performance. This confirms that the entry level continues to have an important weight in subsequent achievements. However, belonging to the experimental group also showed significant predictive value. This indicates that the intervention added explanatory capacity beyond the initial performance. In pedagogical terms, this supports the idea of an intervention organized in phases with neurodidactic mediation and critical incorporation of artificial intelligence. Studies have reported benefits of AI in posing problem activities, practice and support for pedagogical decision-making in future teachers (Al-Shammari & Al-Enezi, 2024; Kim et al., 2025; Kim et al., 2026). This can contribute in an observable way to the strengthening of logical-mathematical thinking in initial teacher training (Yang & Appleget, 2025; Zhang et al., 2025).

The results were also aligned with reviews that have pointed out that AI can contribute to mathematical learning, technological literacy of teachers and didactic planning. However, its effects depend on the institutional context and the purpose for which it is incorporated into the classroom (Kohnke et al., 2025; Panqueban & Huincahue, 2024). They are also compatible with studies that have raised the need to train teachers in frameworks of pedagogical integration of AI. In this way, AI literacy and intelligent TPACK make it possible to avoid superficial or instrumental uses of technology (Ocak & Caskurlu, 2026; Rui et al., 2025). In this context, the contribution of the study is to show that the favourable effect was not observed in an experience of spontaneous use of AI. Rather, it was observed in a sequenced intervention applied in EGB teacher training.

From a theoretical perspective, the findings contribute to the cognitive and neurodidactic frameworks discussed in the introduction by reinforcing the idea that logical-mathematical thinking develops more effectively when reasoning processes are supported through structured mediation, feedback, and progressive abstraction. In relation to Piagetian cognitive development, the results suggest that AI-supported neuroeducation environments may facilitate schema reorganisation and higher levels of formal reasoning through guided interaction and reflective problem-solving activities. Likewise, the findings extend Skemp's notion of relational understanding by showing that mathematical learning improves when students are encouraged to establish conceptual connections rather than merely reproduce procedures (Skemp, 1978).

From a neurodidactic perspective, the results support the argument that executive functions, attentional regulation, metacognitive monitoring, and strategic feedback can be strengthened through pedagogically structured AI-supported activities (Banihashem et al., 2025; Birtwistle et al., 2025). Consequently, the study contributes to expanding current theoretical discussions by demonstrating that the educational value of AI depends less on technological automation itself and more on its integration into cognitively oriented and pedagogically mediated learning environments.

These findings also offer specific implications for curriculum developers, teacher educators, and policy makers. Curriculum developers should consider embedding AI-supported neuroeducational activities into mathematics education courses, not as isolated technological experiences, but as structured components linked to reasoning, abstraction, representation, and problem-solving outcomes. Teacher educators should guide pre-service teachers in the ethical, reflective, and pedagogically justified use of AI tools, with emphasis on feedback analysis, error monitoring, and the design of cognitively demanding mathematical tasks. Policy makers should support institutional frameworks that promote AI literacy, teacher preparation, and responsible digital integration in initial teacher education, ensuring that technological innovation is accompanied by pedagogical quality and curricular coherence.

Despite the relevance of the findings, the study presents some limitations that should be considered. First, the intervention lasted 14 weeks, which makes it difficult to determine the long-term stability of the observed effects on logical-mathematical thinking. Second, the research was conducted within a single institutional context and with a non-probabilistic sample, which may limit the generalisation of the findings to other teacher education programmes or educational realities. Third, although the study focused on quantitative effects, it did not explore in depth the perceptions, experiences, or cognitive processes developed by participants during the intervention. Therefore, future research should consider longitudinal designs with longer intervention periods, replication in different institutional and cultural contexts, and qualitative or mixed-methods approaches aimed at understanding how pre-service teachers experience AI-supported neuroeducational learning environments and how these experiences influence their pedagogical development over time.

In practical terms, the results suggest that initial teacher training can benefit from intervention models. These benefits are more likely when neuroeducation, problem-solving, and artificial intelligence tools are combined under explicit pedagogical criteria. This is not equivalent to replacing the teacher's mediation, but to reinforcing it with resources that help monitor errors, adjust tasks, promote self-regulation and expand opportunities for reflective practice (Rajabi, 2026; Wolff & Martens, 2025; Yılmaz et al., 2026). Hence, the main implication of the study is not technological in the narrow sense, but curricular and formative. Therefore, integrating AI with structure, didactic purpose and ethical criteria can offer better conditions for the development of logical-mathematical thinking in future teachers (Govender & Ramatea, 2025; Kohnke et al., 2025; Sysoyev et al., 2025).

4. CONCLUSION

The study confirmed that neuroeducational methodologies supported by AI had an important effect on the logical-mathematical thinking of teachers in training in EGB. Although both groups indicated comparable levels in the pretest, the experimental group achieved a superior final performance in the posttest. This result was maintained after statistically controlling for the initial score, which supports the existence of an intervention effect.

Linear regression showed that both baseline performance and experimental group membership significantly predicted final performance. Consequently, the findings supported the incorporation of neuroeducational methodologies supported by AI. That is, when organized through a structured didactic sequence, they can contribute to strengthening reasoning, representation, and strategic problem solving in initial teacher education.

In practical terms, the research provides empirical evidence for the EGB career at UTA. In addition, it is suggested to integrate pedagogical proposals with AI from didactic, neuroeducational and ethical criteria. The results supported the alternative hypotheses of the study and provided evidence against the null hypotheses. Both in relation to the effect of the intervention and its predictive value on final performance.

Beyond the technological dimension, the broader significance of the study lies in its contribution to the curricular and formative discussion surrounding teacher education in contemporary contexts. The findings suggest that the educational value of artificial intelligence depends fundamentally on how it is pedagogically integrated into structured neuroeducational environments oriented toward reasoning, reflection, abstraction, and problem solving. Consequently, the study supports the need to prepare future teachers not only to use AI tools, but also to critically and ethically integrate them into mathematics teaching processes capable of strengthening logical-mathematical thinking in school education.

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Declarations

Author Contribution	: MMN-R: Conceptualization, Formal analysis, Methodology, and Writing - original draft; MFQ-B: Investigation, Resources, Supervision, and Writing - review & editing; DM-L: Data curation, Investigation, Validation, and Writing - review & editing; RY-Y: Data curation, Formal analysis, Visualization, and Writing - original draft.
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