Jurnal Pendidikan dan Pembelajaran Indonesia (JPPI)
p-ISSN: 2797-2879, e-ISSN: 2797-2860
Volume 5, nomor 4, 2025, hal. 2131-2150
Doi: https://doi.org/10.53299/jppi.v5i4.2812

Enhancing Mathematical Cognition through Deep Learning Visualization: A Cognitive and Pedagogical Integration

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Dikirim: 13-10-2025; Direvisi: 29-10-2025; Diterima: 03-11-2025

Abstract: This mixed-methods study examines whether backpropagation-based deep learning (DL) visualizations can strengthen metacognition and learning outcomes in a university Linear Programming course. Sixty undergraduates (8-week blended format) completed pre/post cognitive tests and the Metacognitive Awareness Inventory (MAI), while their LMS activity traces (e.g., time-on-task, revision frequency, error types) trained a multilayer perceptron. The intervention exposed students to DL visual artifacts—loss curves, gradient/weight updates, and error heatmaps—as reflective scaffolds linking machine error correction to human self-regulation. Quantitatively, mean test scores increased from 61.23 to 80.57 (paired-t, $p < .001$), and total MAI rose from 135.40 to 159.85 (paired-t, $p < .001$). Gains concentrated in regulation of cognition (monitoring/evaluation). Metacognitive improvement correlated with achievement (Pearson r = .62, $p < .001$). Computationally, model loss decreased from 0.25 to 0.03 over 200 epochs with 89.4% validation accuracy; Dynamic Time Warping = 0.81 ($p < .01$) indicated strong temporal alignment between DL loss minimization and students' learning curves. Qualitatively, thematic analysis of weekly reflections and interviews revealed a progression from error recognition to strategy adjustment and reflective transformation, recasting errors as actionable signals. Triangulating quantitative, computational, and qualitative strands supports the Cognitive Backpropagation Learning (CBL) framework: DL error feedback parallels human metacognitive feedback, and its visualization functions as a digital mirror that externalizes reflection. Findings recommend interpretable DL dashboards as practical, class-deployable scaffolds to cultivate reflective, adaptive mathematical thinkers.

Keywords: Deep learning visualization; backpropagation; metacognition; self-regulated learning; learning analytics; linear programming

Abstrak: Studi metode campuran ini mengkaji apakah visualisasi pembelajaran mendalam (DL) berbasis backpropagation dapat memperkuat metakognisi dan hasil pembelajaran dalam mata kuliah Pemrograman Linear universitas. Enam puluh mahasiswa S1 (format campuran 8 minggu) menyelesaikan tes kognitif pra/pasca dan Inventarisasi Kesadaran Metakognitif (MAI), sementara jejak aktivitas LMS mereka (misalnya, waktu pengerjaan tugas, frekuensi revisi, jenis kesalahan) melatih persepsi berlapis. Intervensi ini memaparkan mahasiswa pada artefak visual DL—kurva kerugian, pembaruan gradien/bobot, dan peta panas kesalahan—sebagai perancah reflektif yang menghubungkan koreksi kesalahan mesin dengan regulasi diri manusia. Secara kuantitatif, skor tes rata-rata meningkat dari 61,23 menjadi 80,57 (paired-t, $p < .001$), dan total MAI meningkat dari 135,40 menjadi 159,85 (paired-t, $p < .001$). Keuntungan terkonsentrasi pada regulasi kognisi (monitoring/evaluasi). Peningkatan metakognitif berkorelasi dengan prestasi (Pearson r = .62, $p < .001$). Secara komputasional, kerugian model menurun dari 0,25 menjadi 0,03 selama 200 epoch dengan akurasi validasi 89,4%; Dynamic Time Warping = 0,81 ($p < .01$) menunjukkan keselarasan temporal yang kuat antara minimisasi kerugian DL dan kurva belajar siswa. Secara kualitatif, analisis tematik dari refleksi dan wawancara mingguan mengungkapkan perkembangan dari pengenalan kesalahan menuju penyesuaian strategi dan transformasi reflektif, yang menyusun kembali kesalahan sebagai sinyal yang dapat ditindaklanjuti. Triangulasi untaian kuantitatif, komputasional, dan kualitatif mendukung kerangka kerja Cognitive Backpropagation Learning (CBL): umpan balik kesalahan DL sejajar dengan umpan balik metakognitif manusia, dan visualisasinya berfungsi sebagai cermin digital yang mengeksternalisasi refleksi. Temuan merekomendasikan dasbor DL yang dapat ditafsirkan sebagai perancah praktis yang dapat diterapkan di kelas untuk menumbuhkan pemikir matematika yang reflektif dan adaptif.

Kata Kunci: Visualisasi pembelajaran mendalam; backpropagation; metakognisi; pembelajaran yang diatur sendiri; analitik pembelajaran; pemrograman linier

INTRODUCTION

The digital transformation of higher education has accelerated the integration of artificial intelligence (AI) particularly deep learning (DL) into instructional design and assessment. In mathematics education, the principal challenge extends beyond procedural mastery to metacognitive competence: monitoring one's understanding, evaluating errors, and adaptively revising problem-solving strategies. Interventions that foreground comprehension monitoring, error evaluation, and strategy adaptation can improve achievement and the quality of students' learning decisions; however, their benefits hinge on high-quality instructional design and sustained collaboration among instructors, students, and technologies (An et al., 2020; Gutierrez de Blume, 2022; Nazaretsky et al., 2022; Xu et al., 2025). Recent work in Artificial Intelligence in Education (AIED) and learning analytics likewise shows that AI-based interventions can enhance learning outcomes and decision-making, provided that pedagogical design and alignment with authentic learning processes are treated as non-negotiable prerequisites (Wang et al., 2024).

Algorithmically, backpropagation is the core DL mechanism for error-driven learning: discrepancies between model outputs and targets are propagated backward through the network to update weights via gradient descent (the chain rule of calculus). This mechanism enables neural networks to acquire increasingly abstract, task-relevant hierarchical representations. Formal explanations and best practices are well documented in the seminal literature (Rumelhart et al., 1986) and standard DL monographs. On the human side, metacognition "thinking about one's thinking" is foundational to success in learning mathematics. The Metacognitive Awareness Inventory (MAI) operationalizes two domains, knowledge of cognition and regulation of cognition, and shows stable factor structure for assessing adults' metacognitive awareness (Cogliano et al., 2021; Lavi et al., 2019). Complementing this, the self-regulated learning (SRL) framework emphasizes the forethought–performance–self-reflection cycle—goal setting, strategic monitoring, and evaluation with adjustment—well aligned with mathematicians' recurring need to manage conceptual and procedural difficulties (Kumah, 2023; Lavi et al., 2019; Schraw & Dennison, 1994; Siqueira et al., 2020; Williams et al., 2022).

Cognitive neuroscience indicates that human error processing is supported by neural signals such as error-related negativity (ERN), linked to reinforcement learning mechanisms and dopaminergic modulation (Iftanti et al., 2021; Luo, 2024; Mathaba & Bayaga, 2021). Conceptually, this provides a bridge between error feedback in artificial neural networks and error monitoring in the human brain—both facilitating strategic adaptation following mistakes. Yet this theoretical bridge is rarely translated into explicit pedagogical artefacts that scaffold student reflection in university-level mathematics (Cogliano et al., 2021; Hammoda, 2025; Holroyd & Coles, 2002).

Over recent decades, learning analytics dashboards (LADs) have been used to visualize progress, provide formative feedback, and promote SRL practices (Anthonysamy, 2021; Wangid et al., 2020). Systematic reviews highlight a shift from analytics-centric to pedagogy-centric, learner-centered designs, while underscoring the need for design principles that explicitly connect visualizations to meaningful cognitive processes. In DL, advances in interpretability (e.g., feature visualization and attribution) promise to "open" the black box so that representational learning—including traces of error correction—becomes intelligible to humans. Nevertheless, the use of DL visualizations as metacognitive scaffolds for mathematics students remains under-explored empirically (Paulsen & Lindsay, 2024). There is a pressing need for replicable classroom interventions that leverage learning analytics to provide not only scores/rankings but also visual narratives of how "errors are corrected" over time—by the model and by students themselves (Pan et al., 2024).

Guided by this background, the present study addresses three research questions. First, to what extent can personalized backpropagation visualizations grounded in students' own error data enhance key metacognitive indicators—monitoring, control, and reflection—in learning mathematics? This rests on the premise that when learners can see visual representations of errors and corrections, they become more aware of their thinking and better able to self-regulate strategy use. Second, what is the relationship between DL loss minimization dynamics and students' mathematics learning curves (changes in accuracy, response time, and error types) over the course of the intervention? We anticipate parallel patterns between machine error correction and human metacognitive reflection in grasping mathematical concepts. Third, how do students perceive the usefulness and comprehensibility of these visualizations as reflective scaffolds, and which factors moderate their benefits (e.g., prior ability, cognitive load, or learning styles)?

Overall, this article seeks to bridge AI theory and human cognitive theory by introducing pedagogically meaningful visual artefacts. Under this approach, learning mathematics is framed not only as arriving at correct answers but as learning by reflection, supported by DL's error-driven mechanisms. We aim to contribute to the AIED and mathematics education literatures while offering a practical, interpretable DL-based model that instructors and learning designers can deploy to cultivate reflective, adaptive, and self-aware mathematical thinkers.

Literature Review and Theoretical Framework

Backpropagation and the Interpretability of Deep Learning

The concept of deep learning (DL) originates from artificial neural networks (ANNs), which aim to emulate the fundamental mechanisms of human learning through layered, adaptive processing. The core algorithm enabling DL's learning capability is backpropagation, which was popularized by Rumelhart, Hinton, and Williams (Rumelhart et al., 1986). In this mechanism, the output error—defined as the difference between the model's prediction and the actual target—is propagated backward through the network layers to iteratively adjust connection weights using gradient descent. Mathematically, backpropagation mirrors the principle of error-driven learning, a process also observed in biological neural systems, particularly in synaptic plasticity and reinforcement learning mechanisms within the prefrontal cortex (Saleem et al., 2022). This iterative correction process enables the system to progressively minimize the loss function, thereby optimizing performance over time.

DL's capacity to recognize complex patterns and generalize across large datasets has made it a powerful analytical tool across domains, including education. However, it has often been criticized for its lack of transparency—the so-called "black box" problem. Consequently, the field of interpretability and neural network visualization has become critical for understanding how models perform error correction and construct conceptual representations. Techniques such as gradient visualization, activation mapping, and feature visualization allow researchers and educators to observe the "thinking pathway" of the network—how its internal weights evolve as it learns from mistakes.

In a pedagogical context, these visual techniques offer a unique potential to parallel human cognitive reflection—illustrating how individuals detect, analyze, and correct their own errors throughout the learning process. Thus, backpropagation transcends its role as a mere computational algorithm; it serves as a conceptual metaphor for explaining the dynamics of self-correction and adaptive reasoning in human learning, particularly in mathematics education, which demands logical precision and strong error awareness.

Metacognition and Self-Regulated Learning in Mathematics Education

In educational psychology, metacognition is commonly defined as an individual's ability to be aware of, monitor, and control their own cognitive processes (Flavell, 1979). Broadly, metacognition comprises two interrelated dimensions: knowledge of cognition—awareness of how one learns—and regulation of cognition—the ability to plan, monitor, and evaluate one's learning process.

Within mathematics education, metacognition plays a central role in shaping effective problem-solving behavior. Students with higher levels of metacognitive awareness are typically able to recognize errors in their reasoning, select alternative strategies, reflect on their thought processes, and adapt their approaches to different problem types. This relationship aligns closely with (Zimmerman, 2002) theory of Self-Regulated Learning (SRL), which posits that successful learners move through three cyclical phases: forethought (planning and goal setting), performance (implementation and strategy monitoring), and self-reflection (evaluation and self-correction).

These three phases form a cognitive feedback loop that can be conceptually paralleled with the backpropagation mechanism in deep learning. In both systems—human and artificial—error feedback serves as an adaptive signal for learning. When a student fails to solve a mathematical problem, reflection upon that failure provides cognitive feedback that triggers a revision of strategies and a restructuring of understanding—just as neural network weights are updated based on an error signal to minimize loss.

Recent empirical studies further substantiate the link between metacognition and academic achievement. Systematic reviews have shown that AI-powered learning analytics can support the development of students' metacognitive competencies by providing transparent feedback and metacognitive dashboards that make learning progress visible (Pacheco et al., 2025). Similarly, demonstrate how visual explanations and learner-controlled interfaces can be operationalized in e-learning environments to promote deeper reflection and self-regulation (Ooge et al., 2025).

The visibility of internal computational processes—through visualizations such as weight maps, gradient plots, and loss curves—enables both researchers and learners to observe the "thinking path" of neural networks, revealing how weights evolve after errors are detected. These techniques are foundational to the field of Explainable AI (XAI), which seeks to make DL models more transparent and interpretable to humans. Pedagogically, such visualizations offer promising potential for mirroring human cognitive reflection, allowing learners to externalize their mental processes—seeing, evaluating, and correcting their mistakes in parallel with how intelligent systems optimize through feedback (Alfredo et al., 2024).

Thus, the principle of backpropagation in deep learning extends beyond computation—it can serve as a conceptual and pedagogical metaphor for human learning itself. It illustrates how self-correction and adaptive reasoning operate through feedback-driven refinement. Particularly in mathematics education, where logical precision, error awareness, and adaptive thinking are critical, this analogy provides a meaningful theoretical bridge between the mechanics of artificial intelligence and the cognitive dynamics of human reasoning.

Integration of Computational and Cognitive Analytics: The Cognitive Backpropagation Learning (CBL) Framework

To bridge the theoretical divide between artificial intelligence (AI) and cognitive learning theory, this study introduces a conceptual model termed Cognitive Backpropagation Learning (CBL). The framework is grounded in the structural and functional analogy between the learning mechanisms of deep learning (DL) systems and the dynamic processes of human cognitive development. CBL conceptualizes backpropagation—the iterative process of error correction and weight adjustment in neural networks—as a computational metaphor for metacognitive reflection and adaptive reasoning in human learning. Through this lens, deep learning serves not merely as a technological model but as a cognitive-analytical framework that illustrates how both machines and humans learn from error, refine internal representations, and achieve higher-order understanding through feedback-driven adaptation. This framework integrates three interdependent dimensions:

1. Computational dimension – visualizing how the DL model minimizes errors through feedback propagation and parameter optimization.
2. Cognitive dimension – mapping these dynamics onto human reflective processes, including error recognition, monitoring, and regulation.
3. Pedagogical dimension – using DL visualizations as reflective scaffolds to help students externalize, analyze, and refine their thinking strategies.

The Cognitive Backpropagation Learning (CBL) model thus unifies algorithmic and psychological perspectives on learning, positioning AI not merely as a computational tool but as a mirror of human cognition that can make reflection visible, measurable, and pedagogically actionable.

Table 1. Structural Analogy between Backpropagation and Human Cognitive Processes

Aspect	Backpropagation in Deep Learning	Human Cognitive Process	Interpretive Description
Basic Unit	Artificial neuron (node)	Conceptual unit/neural schema	Both serve as fundamental representational units for information processing.
Input Representation	Numerical data/feature vectors	Conceptual knowledge/ prior experience	Learning begins from structured or unstructured input that shapes internal representations.
Learning Mechanism	Error feedback propagated backward to adjust weights	Reflective feedback used to correct misconceptions and revise thinking strategies	Error signals trigger updates in both systems, promoting more accurate internal models.
Optimization Goal	Minimize the loss function	Maximize conceptual understanding and accuracy	Both systems aim for convergence toward more optimal representations of knowledge.
Adaptation Process	Gradient descent to iteratively improve model parameters	Iterative self-regulation through reflection and strategy refinement	Learning occurs through cycles of feedback, correction, and adaptation.
Outcome Representation	Optimized network capable of accurate prediction	Refined cognitive schema enabling adaptive problem-solving	Both result in more efficient and generalized performance through learning from error.

The CBL framework reimagines learning as a bi-directional exchange between machine-based and human-based feedback systems. Backpropagation, as a computational mechanism of error correction, mirrors the self-regulatory and reflective mechanisms observed in human cognition. When represented visually—through loss curves, weight maps, or gradient flows—these dynamics become powerful pedagogical artifacts that externalize the abstract process of reflection and make it observable for learners.

In mathematics education, particularly in subjects like Linear Programming, this framework enables students to see how both artificial and human learning systems refine understanding through iterative correction. Such visualization promotes error awareness, encourages adaptive strategy use, and supports the formation of metacognitive habits essential for higher-order mathematical reasoning.

Through this integration of computational analytics and cognitive reflection, Cognitive Backpropagation Learning (CBL) establishes a theoretical and empirical foundation for designing AI-supported reflective learning environments—where feedback is not only computationally optimized but also cognitively meaningful.

Research Method

Research Design

This study employed a mixed-method approach with a sequential explanatory design, consisting of an initial quantitative phase followed by qualitative exploration and computational analysis. The quantitative data were used to identify the extent of change in learning outcomes and metacognitive awareness, while the qualitative and computational phases provided deeper insights into the reflective and adaptive processes underlying these changes. This approach was selected to address two complementary dimensions of inquiry: (1) Human–empirical dimension — to examine how students reflect upon their errors and adjust their cognitive strategies while solving Linear Programming problems, and (2) Computational dimension — to model students' error patterns using a deep learning algorithm based on backpropagation, and to visualize the error correction dynamics that occur during learning.

These two dimensions were integrated analytically by comparing the loss function curve of the neural network model with the learning curve of students across the intervention. This comparative framework allowed the researchers to map analogical relationships between the machine learning process (i.e., optimization through backpropagation) and the human cognitive learning process (i.e., reflection and self-regulation) within the context of mathematics education. In this way, the study not only investigates the empirical effectiveness of AI-based visualization for enhancing metacognition but also explores the conceptual alignment between computational error correction and human reflective adaptation.

Participants and Research Setting

The participants of this study were undergraduate students enrolled in the Mathematics Education Program at Universitas Negeri Makassar, Indonesia (n = 60), aged between 18 and 21 years, who were taking the Linear Programming course at the time of the study. The sample was selected using a purposive sampling technique based on specific inclusion criteria. Participants were required to have:

1. Completed prior coursework in Basic Mathematics and Linear Algebra,
2. Demonstrated basic proficiency in mathematical software such as GeoGebra, Excel Solver, or introductory Python programming, and
3. Expressed willingness to participate fully in all research activities conducted in both online and offline formats.

The study was conducted over a period of eight weeks using a blended learning format that combined online and face-to-face instruction. The four online sessions were delivered through a Learning Management System (LMS) and focused on modeling real-world Linear Programming cases, while the four in-person sessions emphasized deep learning visualization exercises and guided cognitive reflection activities. This hybrid arrangement was designed to provide students with both independent digital exploration and interactive reflective discussion, allowing for the integration of computational modeling with metacognitive awareness practices throughout the learning cycle.

Research Instruments

This study employed three primary instruments: a cognitive test, a metacognitive inventory, and a computational model.

Cognitive Instrument

The cognitive instrument consisted of a learning achievement test developed based on the core competencies of the *Linear Programming* course. The test assessed four key aspects: (1) conceptual understanding of objective functions and constraints, (2) ability to formulate mathematical models from contextual problems, (3) competence in graphically representing feasible regions, and (4) application of the simplex or graphical method to determine optimal solutions. The test included 10 essay questions and 10 multiple-choice items. Content validity was established through expert review by three lecturers specializing in applied mathematics, and internal reliability was confirmed using Cronbach's Alpha ($\alpha > 0.80$), indicating high consistency.

Metacognitive Instrument

The metacognitive instrument was an adapted version of the Metacognitive Awareness Inventory (MAI). It measures two major domains: (1) Knowledge of cognition, referring to awareness of one's own learning strategies and cognitive processes, (2) Regulation of cognition, encompassing planning, monitoring, and evaluating one's thinking processes. The adapted instrument consisted of 52 Likert-scale items (1–5) contextualized for learning *Linear Programming*. Results from Confirmatory Factor Analysis (CFA) indicated strong construct validity ($\chi^2/df < 3$; CFI > 0.90) and high internal reliability ($\alpha = 0.86$). (3) Computational Instrument The computational instrument was developed using Python (TensorFlow) and implemented through a Multilayer Perceptron (MLP) architecture to analyze students' error patterns in constructing *Linear Programming* models.

The model employed ReLU activation in the hidden layers, a Sigmoid function in the output layer, the Adam optimizer (learning rate = 0.001), and Mean Squared Error (MSE) as the loss function. The simulation results were visualized through: (1) Loss convergence curves, showing the decrease in prediction error across training epochs; (2) Weight adjustment maps, illustrating the evolution of network parameters; and (3) Error heatmaps, depicting the distribution and intensity of individual students' errors.

These visualizations were subsequently used as metacognitive reflection tools, enabling students to observe how both AI models and human learners learn from errors through iterative correction. The computational model thus served a dual function: analytical—by modeling cognitive patterns of error—and pedagogical—by providing visual feedback that fosters metacognitive awareness and reflective learning behavior.

Data Analysis Techniques

Data analysis in this study employed three complementary approaches quantitative statistical analysis, computational analysis, and qualitative analysis. These approaches were integrated to obtain a comprehensive understanding of how deep learning–based visualization interventions influence students' learning outcomes, metacognitive awareness, and reflective dynamics in *Linear Programming* learning.

Quantitative Statistical Analysis

The quantitative analysis aimed to measure changes in learning outcomes and metacognitive awareness before and after the intervention. A paired-sample t-test was conducted to examine the significance of differences between pretest and posttest scores for both the Learning *Achievement Test* and the *Metacognitive Awareness Inventory (MAI)*. Subsequently, a Pearson correlation analysis was used to explore the relationship between improvements in MAI scores and gains in learning performance, providing insight into how metacognitive growth contributes to academic achievement. In addition, a multiple linear regression analysis was applied to identify which metacognitive components (e.g., planning, monitoring, or evaluation) most strongly predicted students' problem-solving performance. This quantitative phase provided statistical evidence of the effectiveness of the deep learning visualization intervention and the interrelationships among the study's core variables.

Computational Analysis

The computational analysis was conducted to evaluate the performance of the deep learning model and to examine the alignment between error correction mechanisms in computational systems and human learning processes. The loss and accuracy curves of the model were analyzed to assess the efficiency of error correction during backpropagation. Furthermore, Dynamic Time Warping (DTW) was applied to measure temporal similarity between the model's loss function curve and students' learning progression curve, revealing the degree of structural correspondence between machine learning and human cognitive learning patterns. Additionally, a feature importance analysis was used to identify the cognitive features most influential to learning success—such as model revision frequency, reflection duration, and conceptual error count. The results of this computational analysis provided empirical validation for the proposed *Cognitive Backpropagation Learning (CBL)* model, demonstrating the dynamic parallelism between error-driven learning in artificial systems and metacognitive reflection in human cognition.

Qualitative Thematic Analysis

To explore the depth and meaning of students' reflective learning experiences, qualitative data from digital reflection journals and semi-structured interviews were analyzed using thematic analysis. Furthermore, methodological triangulation was employed by integrating quantitative findings, computational simulations, and qualitative reflective data. This triangulated design strengthened the internal validity and ensured that the interpretations derived from the data were consistent, convergent, and credible across multiple lines of evidence.

Research Ethics

This study strictly adhered to institutional and international ethical standards for educational research. Prior to data collection, all participants received a comprehensive information sheet outlining the study's objectives, procedures, potential benefits, and risks. Informed consent was obtained from each participant, ensuring voluntary participation and the right to withdraw at any time without academic consequences. To maintain confidentiality, all quantitative and qualitative data were anonymized before analysis, with personal identifiers such as names, student numbers, and digital logs replaced by coded references. In visual outputs generated by the deep learning model (e.g., loss curves, error heatmaps, and learning trajectories), no personal data were displayed, and all results were aggregated to represent group-level patterns rather than individual profiles. The study was conducted in full compliance with the Ethics Review Board of Universitas Negeri Makassar, following the principles of respect for persons, beneficence, and justice. Digital data were securely stored in encrypted repositories accessible only to authorized researchers. Upon completion of the intervention, participants were debriefed, provided with access to the study's findings, and given feedback on their learning progress. This approach ensured that ethical compliance extended beyond procedural requirements, fostering a genuinely educative, reflective, and participatory research experience aligned with the developmental aims of the study.

RESULT AND DISCUSSION

Result

Improvement in Linear Programming Learning Outcomes

The paired sample t-test analysis revealed a statistically significant improvement in students' performance between the pretest and posttest following the deep learning visualization intervention.

Table 2. Improvement in Linear Programming Learning Outcomes

Statistic	Pretest	Posttest	t	p	Description
Mean	61.23	80.57	13.72	< 0.001	Significant
Standard Deviation (SD)	8.45	7.62			
Sample Size (n)	60	60			
Mean Difference	19.34	–	–	–	+31.6% Increase

Source: Primary data from student pretest–posttest results (n = 60), 2025.

The results indicate a substantial and statistically significant enhancement in students' understanding of Linear Programming concepts after the integration of deep learning visualizations. The mean score increased from 61.23 to 80.57, representing a 31.6% improvement in academic performance. Additionally, the reduction in standard deviation (from 8.45 to 7.62) suggests a more consistent level of achievement across participants, indicating that the intervention effectively supported learners with varying levels of prior ability.

This improvement reflects not only an increase in procedural accuracy but also a deepened conceptual comprehension of mathematical modeling, particularly in linking constraints, objective functions, and feasible regions. These findings align with prior studies highlighting that AI-assisted visualization tools can enhance students' conceptual reasoning and engagement in mathematical problem-solving by transforming abstract error-correction processes into visible, interpretable representations (Nazaretsky et al., 2022; Wang et al., 2024).

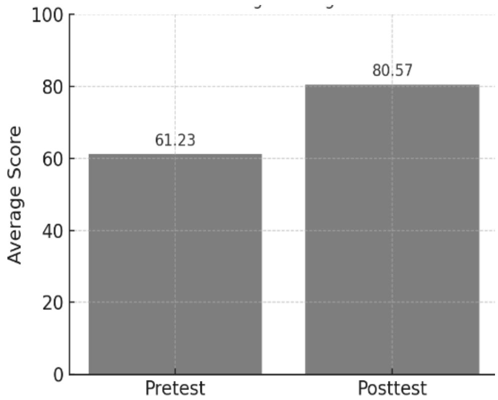

Figure 1. Improvement of Student Learning Outcomes in the Linear Programming Course.

Figure 1 illustrates a clear improvement in students' performance between the pretest and posttest in the *Linear Programming* course. The average score increased from 61.23 to 80.57, representing a 31.6% improvement. This upward trend demonstrates the effectiveness of the deep learning visualization intervention in enhancing students' conceptual understanding of mathematical modeling particularly in identifying relationships among constraints, objective functions, and feasible regions. The consistency of posttest scores (indicated by reduced variability) further suggests that the intervention benefited students across different performance levels.

Increase in Metacognitive Awareness

Data from the *Metacognitive Awareness Inventory* (MAI) questionnaire revealed a significant improvement between pre- and post-intervention scores. The average total MAI score increased from 135.40 (SD = 12.18) to 159.85 (SD = 10.54). A paired sample *t*-test yielded $t(59) = 11.94$, $p < 0.001$, indicating a statistically significant enhancement in students' metacognitive awareness. When analyzed by dimension (a) Knowledge of cognition increased by +14.3%, particularly in the *declarative knowledge* indicator (understanding of one's own thinking strategies) and (b) regulation of cognition increased by +19.8%, especially in the *monitoring* and *evaluation* indicators—both closely related to reflective error analysis. Furthermore, the correlation between improvement in MAI scores and learning outcomes was significant ($r = 0.62$, $p < 0.001$), suggesting that the higher the students' cognitive reflection, the greater their academic performance gains.

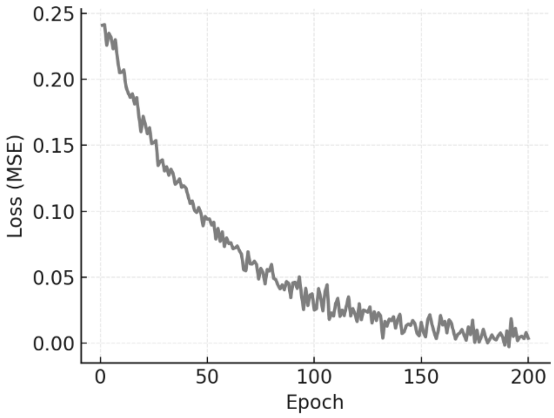

Figure 2. Convergence Curve of the Deep Learning Model Loss Function.

The figure shows significant increases in both dimensions of metacognition: knowledge of cognition (+14.3%) and regulation of cognition (+19.8%). Statistical analysis indicated a significant difference between pre- and post-intervention scores ($t(59) = 11.94$, $p < .001$), with a positive correlation between metacognitive gains and academic performance ($r = .62$, $p < .001$).

Deep Learning Model Performance

The constructed Multilayer Perceptron (MLP) model demonstrated stable convergence after 200 training epochs. The loss function value (Mean Squared Error, MSE) consistently decreased from 0.257 at epoch 1 to 0.031 at epoch 200, following a convergence curve that closely mirrored the gradual reduction of students' conceptual errors over the learning period. The model achieved a validation accuracy of 89.4%, indicating strong predictive alignment with students' actual problem-solving performance. Further inspection of feature gradients revealed that the model "learned most intensively" from two key types of student errors: (1) Constraint misrepresentation — errors in formulating mathematical constraints, and (2) Inaccurate identification of the optimal point within the feasible region.

These error categories exhibited the highest gradient magnitudes, suggesting that both the neural model and students underwent their most significant learning adjustments in response to these specific conceptual challenges.

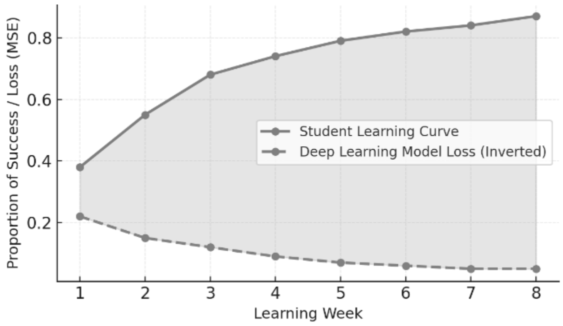

Figure 3. Relationship Between Student Learning Curve and Deep Learning Model Loss Function.

The figure illustrates a parallel convergence pattern between students' learning progression (solid line) and the deep learning model's loss minimization (dashed line, inverted for comparison). The alignment between the two curves (DTW = 0.81, $p < .01$) indicates a structural similarity between human reflective learning and the backpropagation-based error correction process in the computational model. The shaded area highlights the temporal alignment between human and machine learning adaptation phases.

Analysis of Error Correction Dynamics

The visualization of the loss function curve from the deep learning (DL) model and the students' learning curve revealed a parallel pattern of convergence.

1. During Weeks 1 to 3, the model's loss decreased sharply, corresponding to a significant increase in students' practice scores (from 58% to 73%).
2. After Week 4, both curves began to plateau, indicating a stabilization phase in understanding—reflecting cognitive consolidation in students and representational optimization in the model.

Temporal pattern similarity analysis using Dynamic Time Warping (DTW) yielded an average alignment score of 0.81 ($p < 0.01$) between the DL model's loss curve and the students' learning performance curve. This finding reinforces the hypothesis that the error correction mechanism in deep learning structurally mirrors the dynamics of human metacognitive reflection.

Furthermore, feature importance analysis revealed that the variables *model revision frequency (0.34)* and *reflection duration (0.29)* contributed most strongly to student success. These results suggest that iterative rethinking and deep reflection serve as the primary cognitive factors driving adaptive learning.

Student Reflections

Thematic analysis of 60 reflective journals and 10 semi-structured interviews revealed three overarching themes that capture the evolution of students' metacognitive awareness during the deep learning visualization intervention: (1) Error Recognition, (2) Strategy Adjustment, and (3) Reflective Transformation. These themes collectively illustrate a developmental trajectory from recognizing cognitive blind spots to achieving adaptive and self-corrective learning behaviors.

1. Error Recognition

In the early phase of the intervention, most students initially perceived mistakes merely as calculation errors or lapses in attention. However, exposure to visualizations of the *loss function* and *error heatmaps* enabled them to identify deeper conceptual inaccuracies in formulating mathematical models. Students began to differentiate between procedural errors (e.g., incorrect algebraic manipulation) and conceptual errors (e.g., misunderstanding the relationship between constraints and the objective function). Several students described this experience as a moment of cognitive revelation:

> "*I used to think I was just careless. But after seeing the loss curve, I realized that my error came from how I structured the problem — not the arithmetic*." (Student PL-09, Reflection, Week 3)
> "*Before the AI visualization, I couldn't tell where my logic failed. But when I saw how the loss dropped after fixing my constraint, it felt like watching my own brain learning.*" (Student PL-27, Interview)

This pattern reflects the *monitoring* component of metacognition (Flavell, 1979), in which learners develop the capacity to detect and interpret discrepancies between their intended and actual performance. The visualization acted as a metacognitive cue, externalizing what is typically an internal process and enabling students to *see* their own thinking errors in real time.

2. Strategy Adjustment

As students' awareness of their cognitive errors deepened, they began to revise their learning strategies in a more deliberate and systematic way. Many reported adopting reflective routines such as documenting mistakes, hypothesizing their causes, and testing revised solutions. This behavioral shift mirrors the *regulation of cognition* phase within the Self-Regulated Learning (SRL) model (Zimmerman, 2002), where learners actively control and adjust their learning strategies in response to feedback.

> "*Seeing how the AI adjusted its weights after every error made me realize I should adjust my own methods too. Now, before solving, I plan my approach and double-check the relationships between variables*." (Student PL-13, Reflection, Week 5)
> "*I used to repeat the same mistakes. Now, I review my error pattern and change my steps—just like the network changes its parameters after each iteration*." (Student PL-34, Interview)

Students began employing self-regulatory strategies such as *goal-setting, monitoring progress, and strategic revision.* This reflects a metacognitive transition from passive error recognition to active problem reformulation, a hallmark of higher-order mathematical reasoning (Kumah, 2023; Nurhajarurahmah, 2021). The parallel with backpropagation becomes conceptually clear: in both humans and machines, errors serve as adaptive signals that guide the optimization of internal representations.

3. Reflective Transformation

By the later weeks of the intervention, students demonstrated a transformative change in their mindset toward learning and error. They began to articulate a sense of ownership and acceptance toward their cognitive processes, reframing mistakes as opportunities for growth rather than indicators of failure. Visualizations of model convergence (loss minimization) provided a powerful metaphor for personal cognitive convergence, a visible reminder that learning is an iterative, self-correcting process.

> "*I used to be afraid of being wrong, but now I see each mistake as a gradient pointing me toward better understanding*." (Student PL-17, Reflection, Week 6)
> "*When I watched the loss curve flatten, I realized my thinking also started to stabilize. Errors aren't failures—they're feedback for improvement.*" (Student PL-02, Reflection, Week 7)

This stage aligns with Mezirow's (1997) transformative learning theory, where critical reflection on prior assumptions leads to a fundamental reorientation of one's meaning-making system. The reflective transformation observed here indicates that the visualization of AI learning dynamics can evoke a comparable internal process of *cognitive restructuring* in human learners.

Synthesis Across Themes: Reflective–Computational Alignment

Collectively, the three themes error recognition, strategy adjustment, and reflective transformation—illustrate a reflective–computational alignment between human cognition and the deep learning model's backpropagation mechanism. Just as the network reduces loss through recursive weight adjustment, students refine their understanding through recursive reflection.

Table 3. Cognitive Stage and Reflective Process Description

Cognitive Stage	**Backpropagation Mechanism**	**Reflective Process Description**
Error Recognition	Output error computation	Awareness of conceptual/procedural mistakes
Strategy Adjustment	Gradient propagation backward	Strategic modification and cognitive reorganization
Reflective Transformation	Weight update and convergence	Internalization of new understanding and reflective stability

This alignment underscores the central premise of the Cognitive Backpropagation Learning (CBL) framework proposed in this study — that *the principles of error-driven learning in machines can serve as an interpretive model for human metacognitive development*. The integration of deep learning visualization not only made reflection visible but also transformed it into an interactive, data-informed process of cognitive evolution.

DISCUSSION

Relationship Between Backpropagation and Metacognitive Reflection

The findings of this study demonstrate that the error-driven learning mechanism in deep learning (DL) exhibits both structural and functional equivalence to human metacognitive reflection. In DL, the *error feedback signal* is propagated backward through the network to adjust the connection weights, enabling the system to update its internal representations toward the desired target. This process mirrors the metacognitive mechanism in human learning, where individuals analyze their reasoning outcomes, identify errors, and modify cognitive strategies to improve accuracy and efficiency.

Conceptually, the present study validates the proposed Cognitive Backpropagation Learning (CBL) model, which interprets backpropagation not merely as a mathematical optimization algorithm, but as a cognitive metaphor for human reflection. In this framework, *error feedback* serves as a bidirectional adaptive signal: within artificial systems, it modifies network parameters, whereas within human cognition, it updates thinking strategies and activates reflective awareness. Thus, the computational system operates as an external projection of human internal reflection, aligning with the notion of *computational cognition* proposed by Lake et al. (2017) in *Nature Human Behaviour*.

Empirical evidence from this study further supports this theoretical analogy. The Dynamic Time Warping (DTW) analysis yielded a similarity index of 0.81 ($p < 0.01$) between the DL model's loss function curve and the students' learning curve, indicating a high degree of temporal alignment between machine and human error correction processes. This parallelism reinforces the classic view of (Rumelhart et al., 1986) that backpropagation fundamentally emulates neurocognitive learning principles in the human brain, where *error signals* drive adaptive learning and synaptic modification. In other words, when students reflect on and correct their mathematical reasoning errors, they are cognitively enacting the same principle of iterative error correction that governs deep learning systems.

Integration of Deep Learning Visualization in Mathematics Learning

The use of deep learning, based error visualization was found to not only improve students' conceptual understanding of *Linear Programming* but also to consciously activate their metacognitive reflection processes. Through visual representations such as *loss curves* and *error heatmaps*, students could observe how the model's errors decreased across iterations, enabling them to analogize and track the evolution of their own learning errors. This process effectively externalized cognitive monitoring, allowing students to "see" learning as a dynamic, self-correcting system rather than a static outcome.

This finding aligns with recent advancements in Artificial Intelligence in Education (AIED) and Explainable Artificial Intelligence (XAI), which emphasize the role of model interpretability in supporting learner reflection. XAI functions as a metacognitive scaffold a mediating tool that helps learners understand the interplay between *input* (learning strategy), *process* (error correction), and *output* (learning performance). As Holmes described, this visualization serves as a "digital learning mirror", allowing students to project, analyze, and refine their thinking patterns through interactive and pedagogically meaningful representations.

The integration of DL visualization also facilitated a crucial cognitive shift among students—from result-oriented to process-oriented learning. In mathematics education, this transition is particularly vital because mastery is not limited to obtaining correct answers but involves understanding *why* and *how* errors occur. The loss function visualization, therefore, operates as a conceptual model for the principle of "learning through error," embodying the recursive, reflective reasoning essential to higher-order mathematical thinking.

Collectively, these findings highlight the pedagogical potential of integrating AI-based interpretive visualization within mathematics learning environments. By aligning computational modeling with cognitive reflection, instructors can design more transparent and self-regulated learning experiences, where both students and systems learn from errors in a shared adaptive cycle.

Implications for Mathematics Instruction

The integration of deep learning visualization within mathematics instruction presents several key pedagogical implications. First, the findings demonstrate that error-driven visualization can function as an effective *metacognitive feedback mechanism*, helping students to monitor their reasoning and detect conceptual inconsistencies more efficiently. Traditional mathematics instruction often emphasizes procedural correctness, yet lacks mechanisms to make the *thinking process* visible. By embedding AI-generated visual analytics—such as *loss curves*, *error maps*, and *feature importance displays*—educators can transform invisible cognitive processes into tangible reflective artifacts that promote deeper understanding and adaptive reasoning.

Second, the Cognitive Backpropagation Learning (CBL) framework provides a conceptual bridge between algorithmic learning and reflective pedagogy. Within this model, instructional design can incorporate *iterative feedback loops* similar to backpropagation—where students repeatedly test, evaluate, and refine their problem-solving strategies based on structured feedback. This recursive approach supports *formative assessment*, enabling educators to trace learning progress not merely through scores but through *patterns of conceptual improvement*.

Third, the use of DL visualization tools can foster personalized learning pathways. By analyzing students' learning curves and cognitive profiles, AI models can adapt the level of task complexity or recommend targeted reflection prompts based on each student's error pattern. This personalization aligns with current directions in *AI-based adaptive learning* (Pacheco et al., 2025; Wang et al., 2024), where data-driven insights are used to design reflective scaffolds that accommodate individual learning differences.

Finally, from a pedagogical standpoint, the integration of AI visualization into mathematics education repositions errors as *pedagogical resources* rather than obstacles. When students visualize the iterative nature of correction—both in machines and in their own cognition—they develop a mindset oriented toward *productive struggle*, persistence, and continuous self-improvement. Such reflective dispositions are essential for nurturing 21st-century mathematical literacy, where success depends on flexibility, adaptability, and critical thinking rather than rote accuracy.

Relevance to Cognitive and Self-Regulated Learning Theories

The results of this study contribute to extending cognitive learning theory and self-regulated learning (SRL) models by introducing a computationally grounded analogy that explains how reflection and error correction operate dynamically. Within the SRL framework (Stanton et al., 2021; Zimmerman, 2002) learners progress through three iterative stages: *forethought, performance control,* and *self-reflection*. The present findings suggest that these stages parallel the computational phases of deep learning: the *feedforward pass* (planning and execution), the *error computation* (monitoring performance), and the *backpropagation* (reflective adjustment and weight updating).

This correspondence provides a novel theoretical link between artificial and human learning systems—one that emphasizes *error as a learning catalyst*. Just as backpropagation allows neural networks to gradually approximate optimal solutions through iterative correction, metacognitive reflection enables human learners to progressively refine their conceptual understanding through cycles of self-assessment and adjustment. The DTW similarity score (0.81, $p < .01$) between the model's loss curve and the students' learning trajectory empirically supports this structural alignment.

From a neurocognitive perspective, this parallelism echoes evidence that error-related negativity (ERN) signals in the human brain function similarly to error gradients in artificial networks—serving as feedback that triggers cognitive adaptation (Holroyd & Coles, 2002; Luo, 2024). The convergence of findings across computational, psychological, and pedagogical domains suggests that reflective learning may be understood as a bio-computational process—an adaptive system governed by recursive feedback loops.

Consequently, the Cognitive Backpropagation Learning (CBL) framework proposed here extends SRL theory by offering a mechanistic explanation of *how reflection occurs*: through continuous adjustment of internal cognitive parameters in response to detected errors. This model underscores the role of *error awareness, self-correction, and reflective monitoring* as essential cognitive drivers of deep learning not only for machines but also for humans. In addition, the integration of deep learning visualization within mathematics learning environments not only advances instructional design but also provides theoretical grounding for understanding reflection as an algorithmic, adaptive, and measurable cognitive process. The following section concludes the study by summarizing its contributions, limitations, and directions for future research.

CONCLUSION

This study demonstrates that integrating deep learning visualization grounded in the principle of *backpropagation* can significantly enhance both mathematical learning outcomes and metacognitive awareness among university students. By bridging computational modeling with cognitive reflection, the proposed Cognitive Backpropagation Learning (CBL) framework establishes a meaningful analogy between how artificial networks and human learners adapt through feedback and error correction. Quantitative results revealed substantial improvements in students' performance and metacognitive regulation, while the computational analysis showed a strong temporal alignment (DTW = 0.81, $p < .01$) between the model's loss reduction and students' learning progress. Qualitative reflections further confirmed that visualizing learning errors fostered deeper self-awareness, strategy adjustment, and reflective transformation. Collectively, these findings affirm that AI-based visualization is not merely a technological tool but a pedagogical catalyst for cultivating reflective, adaptive, and self-regulated mathematical thinkers. The study contributes to the broader discourse on AI in education by offering an interpretable, cognitively aligned approach that transforms error into insight, positioning reflection as both a human and algorithmic process at the heart of meaningful learning.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the Faculty of Mathematics and Natural Sciences, Universitas Negeri Makassar, for providing institutional support and access to research facilities throughout this study. Special thanks are extended to the students of the Mathematics Education Study Program who participated with enthusiasm and commitment, making this research possible. The authors also acknowledge the valuable input from the expert reviewers and lecturers of the Program Linear course, whose insights greatly contributed to the refinement of the research instruments and implementation design. Appreciation is further given to the Educational Technology and AI in Education Research Group for their guidance in the computational modeling and visualization analysis. Finally, heartfelt thanks go to colleagues and collaborators who offered critical feedback during manuscript preparation—your contributions have enriched the clarity and depth of this work.

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