The Mathematics Education **ISSN 0047-6269**
Volume-LIX, No. 4, December 2025
Journal website: https://internationaljournalsiwan.com/Mathematic.php
ORCID Link: https://orcid.org/0009-0006-7467-6080
International Impact Factor: 7.75 https://impactfactorservice.com/home/journal/2295
Google Scholar: https://scholar.google.com/citations?hl=en&user=UOfM8B4AAAAJ
Refereed and Peer-Reviewed Quarterly Journal

Enhancing Conceptual Resilience Through Timed Lateral Scaffolds: A Study of AI-Supported Learning

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(Received: November 18, 2025; Accepted: December 1, 2025;
Published Online: December 31, 2025)

Abstract:

Advances in Artificial Intelligence (AI) technologies have made it possible for us to develop intelligent tutoring systems that are capable of adapting dynamically to learners' needs. But existing systems are able to provide step-by-step or hierarchical support, they often do not take into account-the lateral dimensions of problem solving, which is how learners form horizontal conceptual connections as they work through complex tasks. This proposed system would be continuously analysing the problem-solving trajectory of the learner in real-time by monitoring indicators, such as response latency and error clustering, to detect points of stagnation. Following the inference of a learning impasse, the AI would *interfere but not by simplifying the task; instead, it reorients the student toward related or adjacent concepts to encourage associative reasoning rather than linear hint-giving. Thus, the horizontal guidance allows the learner to draw conceptual parallels, recognize underlying patterns, and reconstruct understanding without disrupting autonomy. A controlled experiment of 360 undergraduate mathematics students tested three scaffold delivery modes, namely early, mid process, and late, to examine how timing influences learning. Quantitative data on accuracy, time-on-task, and cognitive load were complemented by interview data on metacognitive awareness and confidence. The results indicated that timing-sensitive lateral scaffolding enhances conceptual retention and problem-solving resilience. Rather than providing answers, the AI tutor acts like a cognitive companion by aligning support with the learner's thought process. This study advances scaffolding theory by adding a temporal-lateral dimension, showing how AI can assist at the precise moment of conceptual struggle, shifting tutoring from reactive to proactive support.*

Introduction:

Recent years have seen phenomenal growth in the area of Artificial Intelligence (AI), which has helped in the advancement of educational technology and popularization of intelligent tutoring systems (ITS) that can provide adaptive, personalized learning experiences. Similarly, modern AI tutors, use large language models along with real-time analytics to analyze the performance of students, identify misconceptions and provide step-by-step guidance comparable to that provided by human instructors. Recent works such as the CLASS (Sonkar et al., 2023) and dynamic the ITS architectures (Anwar et al., 2022) show a significant gain in efficiency and engagement in scaffolding systems in AI tutoring. Despite these accomplishments in state-of-the-art systems fall short in one critical dimension i.e. most existing AI tutors decide what scaffolds to deliver but not when to deliver them, they typically trigger hints after repeated errors or fixed intervals. This lack of temporal awareness disrupts natural problem-solving rhythms because interventions either arrive too early or too late to preserve the learner's cognitive flow. Scaffolding, stemming from Vygotsky's Zone of Proximal Development, is one of the most important constructs to advance independent learning. Scaffolding refers to the temporary, adaptive support which guides complex tasks for learners until such time as they are able to perform them autonomously. Well-timed scaffolding enhances motivation, engagement, and metacognitive awareness, while ill-timed scaffolding threatens either cognitive overload or disengagement. The newly developed lateral scaffolding framework by Pranav Srinivas & Gireesh D.S. (2025) extends this concept horizontally. It thus places greater emphasis on conceptual associations across related ideas than hierarchical task simplification. This approach thus helps foster meaningful cognitive links among learners for deeper understanding and flexible reasoning.

This research extends this theoretical framework by exploring temporal-lateral scaffolding. Where an AI tutoring system considers not only what type of scaffold to provide but also when, in light of temporally unfolding learning indicators, including response latency and error clustering. We predict that time-sensitive lateral scaffolds will increase conceptual retention, reduce cognitive friction, and facilitate self-regulated problem-solving. The expected outcome of this study will be a validated computational model of sensitivity to temporal scaffolding along with practical design guidelines for AI-based adaptive tutoring systems.

Related Works:

Several studies have been conducted recently that contribute to the growing understanding of adaptive and AI-driven scaffolding in educational contexts Srinivas and Gireesh (2025) introduced lateral scaffolding focus. The study established horizontal conceptual associations between main topics and subtopics instead of succeeding along gradually more difficult tasks as hierarchically organized. Their findings highlight timing, reflection, and global problem representation and are the theoretical basis upon which this research is built as it extends their findings via adaptive timing. Sonkar et al. (2023) introduced the CLASS framework, an LLM-backed Intuitive tutoring system that implements dynamic and conversational scaffolding for learner engagement and improved adaptability. This study offers insights into scaffolding logic integration into AI-driven tutoring systems. Anwar et al. (2022) studied real-time dynamic scaffolding during tutoring sessions, finding that providing more effective interventions through adaptation drastically improved learner performance and made system authorship easier, thus supporting this project's real-time intervention model. Li et al. (2025) explored a real time learning analytics model through a generative AI to create an adaptive self-regulated learning scaffolds that adjusts through the cognitive load and the learner answer reaction time thus providing an empirical basis for machine learning based predictive models in adaptive tutoring. Faber et al. (2024) studies control between adaptive and fixed scaffolding this study found that adaptive scaffolding reduces cognitive load and also helps increases efficiency by leveraging learner engagement thus the individualized use of timing, adaptivity are substantiated. Gürel (2025) studied contingent scaffolding in mathematical modelling. The study found that post-completion scaffolds given at the right time and succeed across sessions in enhancing long term modelling competence thus emphasizing carry-over effects and a relative temporal placement of scaffolds across sessions. Li and Wilson (2025) discussed AI integrated scaffolding that not only balances cognitive, creative as well as linguistic support this study emphasizes AI guidance should be used to enhance rather than restrict learner autonomy.

Together, all these studies give us a comprehensive foundation for the development of a adaptive scaffolding systems that is ethically guided and emotionally engaging and is capable of optimizing timing and reducing cognitive load while fostering both learning outcomes and learner agency.

The proposed temporal lateral scaffolding framework in the above image and provides contextually appropriate and temporally sensitive instructional support. This study is grounded in Vygotsky's theory of Proximal Development and also the lateral scaffolding approach introduced by Srinivas and Gireesh D.S. (2025). Unlike traditional scaffolding, which operates vertically-moving from simple to complex tasks, the lateral approach to scaffolding concerns horizontal connections among ideas and fosters rebuilding understanding through association rather than repetition. In the process, the learner's problem-solving activity is continuously monitored to pinpoint the very moment when he or she gets cognitively "stuck." Rather than giving an answer, the system detects when comprehension breaks down and provides conceptual cues that assist the learner in reconnecting ideas laterally. In this way, it ensures that support is provided right at the moment when the learner needs it-neither a moment too soon nor after the cognitive momentum has been lost-so engagement and autonomy are preserved.

Framework Proposed:

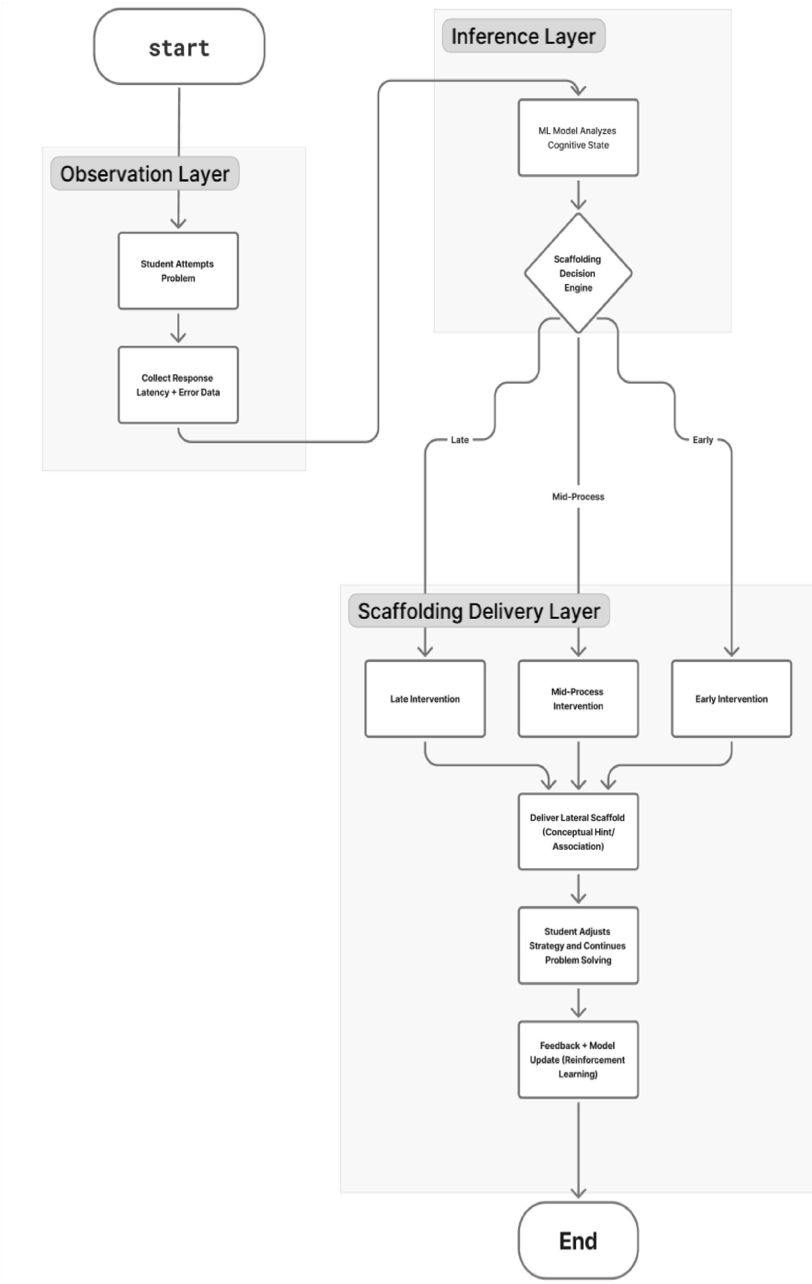

Figure 1: Flowchart Representing the Proposed Framework

The adaptive tutoring prototype described in the study operationalizes this conceptual model with an integrated machine learning algorithm that performs real-time analysis of student performance. The two most salient behavorial signals analysed are response latency and error clustering. Response latency refers to the time between the appearance of a problem and the learner's response serves as a variable for hesitation or cognitive overload. An increase in latency indicates that the student has conceptual difficulty. Error clustering refers to the density of successive mistakes and reflects confusion or misunderstanding of the concepts. The AI continuously assesses these two metrics to make inferences about the learner's cognitive state, deploying pattern recognition to determine when and where an impasse occurs. Once a learning bottleneck has been detected, the system retrieves an optimal scaffolding response that is matched not only to problem type but also to the timing of the difficulty. This diagnostic capability transforms the tutor from a reactive tool into a proactive learning companion able sense and respond to the learner's cognitive trajectory. Scaffold delivery occurs through three temporal intervention modes: early, mid-process, and late intervention.

Early intervention is always preventive, and it is triggered when, through rising response latency, the system detects early signs of hesitation or cognitive delay. The AI thus provides light lateral cues-guiding questions-to maintain problem solving flow. Mid-process intervention occurs when the learner makes repeated errors and has prolonged hesitation in solving a problem. It is also signaled by significant error clustering. For this the system introduces lateral hints that link the current concept to related foundational ideas helping the student reframe the problem and regain conceptual progress. Late intervention is always reflective and delivered after the task is completed this always indicates persistent difficulty and a significant error clustering. Here the AI helps consolidate learnings by explaining alternative solutions and paths and reinforcing the learners conceptual associations. These interventions thus create a continuous cycle of observations, analysis, and build an adaptive response, ensuring that the scaffolding remains both temporally precise and conceptually supportive for the learner.

Experimental procedure:

The experiment was conducted with 360 undergraduate mathematics students in their first and second years of study, where all had completed introductory algebra and provided informed consent. Participants were stratified by GPA and pretest scores from a 15-item mathematics assessment to ensure balanced prior knowledge before being randomly assigned to one of three groups: Early (preventive), Mid-process (responsive), and Late (reflective) scaffolding conditions (n = 120 per group). The study followed a pattern between-subjects design, manipulating only the timing of scaffold delivery while keeping the content and task difficulty constant. Each participant solved nine multi-step mathematical problems covering algebra, functions, and introductory calculus. Problems were presented through a computer-based learning environment (CBLE), which automatically recorded accuracy, timestamps, response latency, and hint usage. Scaffolds were designed to be lateral-prompting conceptual associations, analogies, or guiding questions-rather than direct procedural steps to encourage reasoning over rote application. Timing of the scaffolds was controlled algorithmically. In the early condition, scaffolds appeared immediately after a first response or at Step 2 of a problem as preventive conceptual cues. In the adaptive mid-process condition, scaffolds were triggered when two consecutive errors were made or when response latency exceeded +1.5 SD above a learner's baseline (indicating cognitive hesitation / confusion). For the late condition, scaffolds were shown only at the end of a problem or after four errors, thus serving as reflective feedback. Each student participated in two sessions. Session 1 (Day 1) included consent, a pretest, system tutorial, and two problem-solving blocks separated by a short confidence survey; students rated mental effort invested using the Paas scale 1-9 after each problem. Session 2 (Day 8 ± 1) consisted of a retention test with isomorphic problems and a transfer task applying learned concepts to novel contexts, followed by semi-structured interviews (subset $n \approx 60$) on perceptions about timing, metacognition, and confidence. Some primary measures were accuracy, time-on-task, and retention scores. Secondary metrics assessed cognitive load and post-scaffold performance gains and latency/error-clustering dynamics. Qualitative interviews provided the context that complemented quantitative data. Trials with idle gaps that were > 120s or technical issues were excluded, and latency values were analysed to remove outliers. Data was analysed using mixed effects models with the participant for the retention and the transfer analyses. Planned contrasts compared the early, mid, and the late groups, while qualitative data were subjected to thematic coding. Both the participants and the facilitators were blind to the condition and the hypothesis. With 120 students per group, power analysis confirmed ≥ 80% power to detect medium effects (≈ 6-8 pp accuracy gain, $d \approx 0.25$-0.30). The safeguards included limiting scaffolding to one intervention per problem to avoid over-assistance, and late-phase reflective scaffolds were used to ensure that every learner received conceptual reinforcement.

Task Accuracy:

$$A_i = \frac{C_i}{N_i} \times 100$$

Where: A_i = Accuracy (%) for learner i; C_i = Number of correct responses; N_i = Total number of problems attempted

Response Latency:

$$L_{ij} = t_{end} - t_{start}$$

Where:

L_{ij} = Response latency for learner i on problem j
t_{start} = Timestamp when problem j is presented
t_{end} = Timestamp when the learner submits a response

Latency Deviation (Trigger Threshold):

$$Z_{L_{ij}} = \frac{L_{ij} - \bar{L}_i}{\sigma_{L_i}}$$

Where:

$Z_{L_{ij}}$ = Standardized latency score (Z-score)
$\bar{L}_i$ = Mean latency across previous problems for learner i
σ_{L_i} = Standard deviation of latencies for learner i

Error Clustering:

$$C_{E_i} = \frac{E_{window}}{N_{window}}$$

Where:

C_{E_i} = Error cluster ratio for learner i
E_{window} = Number of incorrect responses within a rolling window
N_{window} = Total responses in that window

Cognitive Load:

$$CL_i = \frac{\sum_{j=1}^{n} S_{ij}}{n}$$

Where:

CL_i = Mean cognitive load score for learner i
S_{ij} = Subjective rating of mental effort on problem j (1-9 scale)
n = Number of problems attempted

Retention and Transfer:

$$R_i = \frac{S_{retention}}{S_{post}} \times 100$$

$$Tr_i = \frac{S_{transfer}}{S_{post}} \times 100$$

Where:

R_i = Retention percentage for learner i
Tr_i = Transfer performance for learner i
S_{post} = Post-test score
$S_{retention}$ = Retention test score
$S_{transfer}$ = Score on transfer problem

Image 1: List of Formula used in calculations

Results and Discussions:

The results show that timing is very important for the success of scaffolding interventions. All groups received the same lateral content but the mid process (responsive) scaffolds showed the best learning results, the least cognitive load, and the best retention. This corroborates our studies primary hypothesis that the timing of scaffolding is as significant as its content.

Metric	Early	Mid-Process	Late	Key Insight
Accuracy (%)	74.8	**81.4**	76.1	Mid-process timing yields highest success
Time-on-Task (min)	7.4	**6.7**	7.9	Timely scaffolds reduce effort duration
Cognitive Load (On a scale of 1-9)	4.9	**4.1**	5.3	Mid-process scaffolds minimize overload
Retention (%)	71.3	**78.5**	73.0	Adaptive timing enhances long-term retention
Transfer (%)	70.2	**74.6**	71.5	Learning generalizes across tasks

Table 1: Results obtained and its Key Insights

Early interventions, while well-meaning, may disrupt cognitive exploration too soon, resulting in shallow engagement. Late scaffolds, on the other hand, give people a chance to think about things, but they don't help when people really need help, which makes their real-time impact less. The better results of the mid-process condition show that scaffolding works best when it fits with the learner's natural way of solving problems, right when cognitive tension is at its highest but before frustration sets in.

The mediation results shed light on the underlying mechanism: adaptive timing controls cognitive load by reducing error clustering and spikes in response latency. When scaffolds are aligned with cognitive load, learners experience enhanced cognitive fluidity, engage in more profound reasoning, and develop more robust conceptual frameworks. This finding corroborates cognitive load theory (Sweller, 2010) and introduces a temporal-lateral dimension, demonstrating that instructional timing and conceptual directionality collectively influence learning efficiency.

Theoretically, this study enhances Vygotskian scaffolding and Srinivas & Gireesh's lateral scaffolding framework by incorporating real-time adaptivity and temporal sensitivity. From an educational point of view, it says that AI tutors should be cognitive companions instead of just giving answers. They should keep an eye on engagement, look for cognitive friction, and step in with associative cues at the right times. The consequences are important for intelligent tutoring systems, adaptive learning platforms, and the design of education. This framework can help next-generation AI tutors that can offer proactive, insight-driven support by showing how and when scaffolds should happen.

Limitations:

While these results serve as very strong evidence in support of effective timing-sensitive lateral scaffolding, there are a number of limitations that must be acknowledged.

Firstly, the problem solving strategies when it comes to mathematical problems vary greatly across learners and topics as there is a wide variation in prior experience, favoured heuristics, and individual reasoning patterns. The general training of the system's machine learning model is based on a number of general performance indicators such as response latency and error clustering may not fully capture the nuances of different problem-solving methodologies. Secondly, since cognitive ability and IQ varied across the sample, both rates and depths of conceptual understandings are likely to differ. While randomization generally balanced these groups, some innate differences in analytical capacity and working memory may have potentially influenced responsiveness to scaffolding. Thirdly, mathematics as a discipline is cumulative in nature; each new concept rests on prior knowledge. Any weakness in foundational concepts, such as algebraic manipulation or function interpretation, could distort the effectiveness of scaffolding in higher-level problems because the AI tutor assumes a certain baseline level of competencies hence prior differences in mastery may have confounded learning outcomes despite pretesting controls. This was a study carried out in a controlled experimental setting so actual classroom conditions involve more variables, including peer interaction, motivation, and time constraints. These factors are suggested for future large-scale or longitudinal validation.

Conclusion:

The proposed temporal-lateral scaffolding framework illustrates how adaptive AI systems align instructional support with the learner's current cognitive state in a way that improves accuracy, retention, and engagement by combining timing sensitivity with lateral conceptual guidance; this helps learners where they are most likely to struggle and strengthens their ability to connect meaningfully related concepts.

Beyond this experimental setting, the framework shows very good potential in being applicable for primary and lower elementary education, as the foundational understanding is critical at this stage. Moreover, the focus of the framework on personalized instruction makes it flexible to correspond to individual learning styles, cognitive speeds, and problem-solving strategies. By incorporating real-time analytics along with customized feedback, it fosters continuous engagement, even after school, for self-learning and at one's own pace. Overall, the temporal lateral scaffolding model offers everyone a guideline for next-generation intelligent tutoring systems that will be more capable of facilitating conceptual continuity, personalization and lifelong learning habits thus making sure students not only learn but truly understand and remember what they learn.

Conflicts of Interest:

The authors declare that they have no conflicts of interest.

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