AI-Driven Support for Teaching Mathematical Concepts in Engineering Subjects to Academically At-Risk Students

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ABSTRACT:

Mathematical competence is essential for engineering subjects such as circuit analysis, signal processing, fluid mechanics, heat transfer, control systems, and structural analysis. However, some students require additional instructional time, repeated practice, and multiple representations before they can confidently connect mathematical procedures with engineering meaning. This paper presents an evidence-based narrative review of artificial intelligence (AI) support for teaching mathematical components of engineering subjects to such learners. The paper contributes a focused synthesis of AI-supported mathematics learning in engineering contexts and proposes a human-in-the-loop framework with neuro-symbolic verification and scaffold fading. The manuscript does not report empirical classroom results; instead, it integrates literature on intelligent tutoring systems, Bayesian and deep knowledge tracing, cognitive load theory, universal design for learning, learning analytics, and generative AI. The review indicates that AI may support prerequisite diagnosis, adaptive sequencing, worked-example practice, formative feedback, and teacher alerts when used as a supervised support layer rather than as a replacement for teachers. Key safeguards include mathematical verification, learner privacy, avoidance of permanent deficit labels, culturally inclusive examples, and gradual reduction of AI support to promote independent problem solving. The proposed framework and implementation plan are intended for the future empirical validation in engineering education.

Keywords: Artificial intelligence in education; engineering mathematics; intelligent tutoring systems; Bayesian knowledge tracing; learning analytics; generative AI; inclusive engineering education; scaffold fading; neuro-symbolic verification.

1. Introduction

Engineering education depends heavily on mathematical understanding. Students are expected to use calculus, differential equations, linear algebra, vector calculus, probability, and statistics across core subjects rather than as isolated topics. For example, differential equations are needed in circuit transients, heat transfer, vibrations, and control systems; vector calculus is central to fluid mechanics and electromagnetics; and linear algebra supports robotics, structural analysis, data-driven control, and machine learning applications.

The term 'slow learner' appears in some institutional contexts, but it must be handled carefully. In this manuscript, it does not denote a medical or fixed cognitive category. It refers only to students who require more time, guided practice, prerequisite repair, or alternative representations to master mathematical ideas used in engineering subjects. The preferred wording in the paper is 'students requiring additional learning support' because it avoids deficit-based labelling.

AI-enabled learning environments are relevant because they can provide individualized pacing, immediate feedback, analytics-based early alerts, and repeated practice without embarrassment. However, AI can also introduce risks: inaccurate generated explanations, overdependence, privacy concerns, algorithmic bias, and reduced teacher oversight.

Therefore, this paper argues for AI as a supervised support layer in engineering mathematics education, not as an autonomous substitute for teachers.

2. Method and Scope of the Review

This paper does not report an empirical classroom intervention or student-performance dataset; rather, it synthesizes prior literature and proposes a conceptual framework for future validation.

A targeted narrative search was used to identify foundational and recent sources relevant to AI-supported mathematics learning in engineering education. The search emphasized publications from 1994 to 2024 and used combinations of terms such as 'intelligent tutoring systems', 'Bayesian knowledge tracing', 'deep knowledge tracing', 'engineering mathematics education', 'cognitive load', 'universal design for learning', 'learning analytics', 'generative AI in education', and 'hallucination in natural language generation'. Sources were identified through publisher platforms, academic search engines, and authoritative organizational websites. Priority was given to peer-reviewed empirical studies, review articles, established books, and policy guidance. The search was not intended to be exhaustive and is therefore presented as a narrative review rather than a systematic review.

No primary student dataset was collected for this draft. Consequently, the manuscript does not report learning gains, statistical significance, sample size, intervention duration, or institutional outcomes. All claims about educational impact are therefore framed as possibilities or design implications based on existing literature, not as proven effects of the proposed framework.

3. Literature Foundation

3.1 Intelligent Tutoring and Knowledge Tracing

Intelligent tutoring systems (ITS) are among the most established forms of AI in education. VanLehn reviewed evidence comparing human tutoring, computer tutoring, and other tutoring systems and emphasized that tutoring effectiveness depends on feedback quality, step-level support, and instructional design rather than technology alone [1].

In engineering mathematics, this is important because learners often need feedback not merely on final numerical answers but also on intermediate mathematical reasoning.

Knowledge tracing provides another important foundation. Corbett and Anderson modelled how a student's procedural knowledge changes over time during skill acquisition [2]. Bayesian Knowledge Tracing (BKT) remains a widely implemented approach that estimates student mastery probabilistically across knowledge components [2], while Deep Knowledge Tracing uses recurrent neural networks to model learning sequences and may offer stronger prediction in some datasets at the cost of interpretability [3].

For students needing additional learning support, interpretability matters because teachers must understand why a system recommends remedial practice. Explainable AI (XAI) techniques are therefore relevant for making diagnostic alerts and sequencing decisions more understandable to teachers rather than treating the model as an opaque authority.

3.2 Cognitive Load and Inclusive Design

Cognitive load theory explains why learners can fail when instructional material exceeds working-memory capacity. Sweller, Ayres, and Kalyuga describe cognitive load theory as an instructional-design framework for managing intrinsic, extraneous, and germane load [4]. Paas, van Gog, and Sweller further emphasize methods for managing working-memory load in complex learning tasks [5]. Engineering mathematics is cognitively demanding because learners must coordinate notation, procedures, diagrams, units, and physical interpretation.

Universal Design for Learning (UDL) is also relevant. CAST describes the UDL Guidelines as a framework for improving and optimizing teaching and learning for all learners and released UDL Guidelines 3.0 in 2024 [6].

For engineering mathematics, UDL implies multiple means of representation, engagement, and action: a derivative may be explained symbolically, graphically, verbally, and through an engineering example such as rate of change in a transient response.

3.3 Learning Analytics, Generative AI, and Verification

Educational data mining and learning analytics can identify learners who may need early support. Baker and Inventado describe educational data mining and learning analytics as related areas concerned with using educational data to understand and improve learning [7]. Romero and Ventura provide an updated survey of educational data mining and learning analytics methods [8]. In engineering mathematics, early alerts may be useful when students show persistent errors in prerequisites such as algebraic manipulation, trigonometry, integration, or matrix operations.

Generative AI offers new forms of conversational scaffolding. UNESCO's guidance on generative AI in education emphasizes a human-centred approach and identifies risks to inclusion, equity, agency, and linguistic and cultural diversity [9]. Kasneci et al. discuss both opportunities and challenges of large language models in education [10].

A specific concern for engineering mathematics is hallucination: generated output may be fluent yet mathematically incorrect or unsupported. Ji et al. define and review hallucination in natural language generation [11].

This reinforces the need for verification layers in any AI tutoring system that generates mathematical explanations, derivations, or engineering interpretations.

4. AI Interventions for Engineering Mathematics

Table 1 summarizes how selected AI methods can support mathematical components embedded in engineering subjects. The examples are illustrative and should be validated in real classroom implementation before effectiveness claims are made.

Mathematical component	Engineering context	AI support function	Differentiation strategy for students needing support	Safeguard
Algebra and functions	Circuit analysis, control-system transfer functions	Worked examples, error diagnosis, prerequisite repair	Breaks multi-step operations into two or three sub-steps; highlights transition points and common sign errors	Temporary prerequisite-gap alerts; teacher review of recurring errors
Differential equations	Heat transfer, vibrations, transient circuits	Step-level hints and adaptive sequencing	Starts with separable/first-order cases before moving to boundary-value or Laplace-transform tasks	Temporary prerequisite-gap alerts; symbolic checking of solution steps
Linear algebra	Structural matrices, robotics kinematics, state-space models	Visual and procedural scaffolding	Links row operations, matrix meaning, and engineering interpretation through diagrams and short exercises	Cognitive-load control and teacher override of alerts
Vector calculus	Fluid mechanics, electromagnetics	Multimodal explanations and diagram-based prompts	Connects gradient, divergence, and curl to field diagrams and physical examples	Checks notation, units, and assumptions
Probability and statistics	Quality control, communication systems, reliability	Learning analytics and mastery tracking	Repairs gaps in combinatorics and distributions before stochastic-process examples	Uses temporary alerts, not permanent labels

Table 1. Illustrative AI support roles for mathematical components of engineering subjects. The table describes intended instructional roles and safeguards; it does not report measured effectiveness.

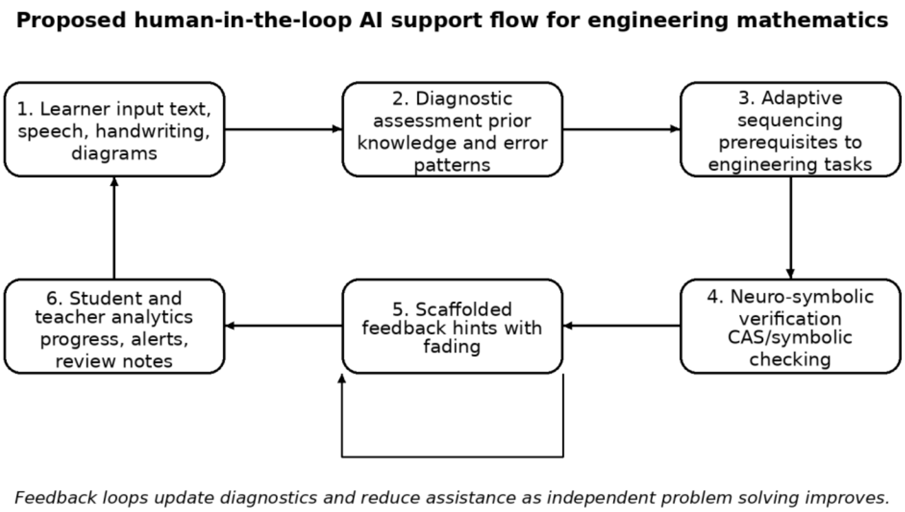

Fig. 1. Proposed human-in-the-loop AI framework for engineering mathematics support. The diagram shows sequential operation with feedback loops and verification before feedback is returned to learners.

5. Research Gaps

Four gaps appear repeatedly across the reviewed literature and are especially relevant to engineering mathematics. First, many tools do not sufficiently manage cognitive load. A learner who is already struggling with notation may be further overloaded by cluttered dashboards, excessive hints, or split attention between symbolic derivation, calculator output, and chat windows. Second, generative AI can produce explanations that sound plausible but contain wrong algebra, missing assumptions, or incorrect engineering interpretation. Third, predictive analytics may create unfair tracking if early weakness is treated as a fixed identity rather than a temporary support need. Fourth, many AI learning interventions are evaluated over short periods; engineering education needs longitudinal evidence that students can solve problems independently when AI assistance is removed.

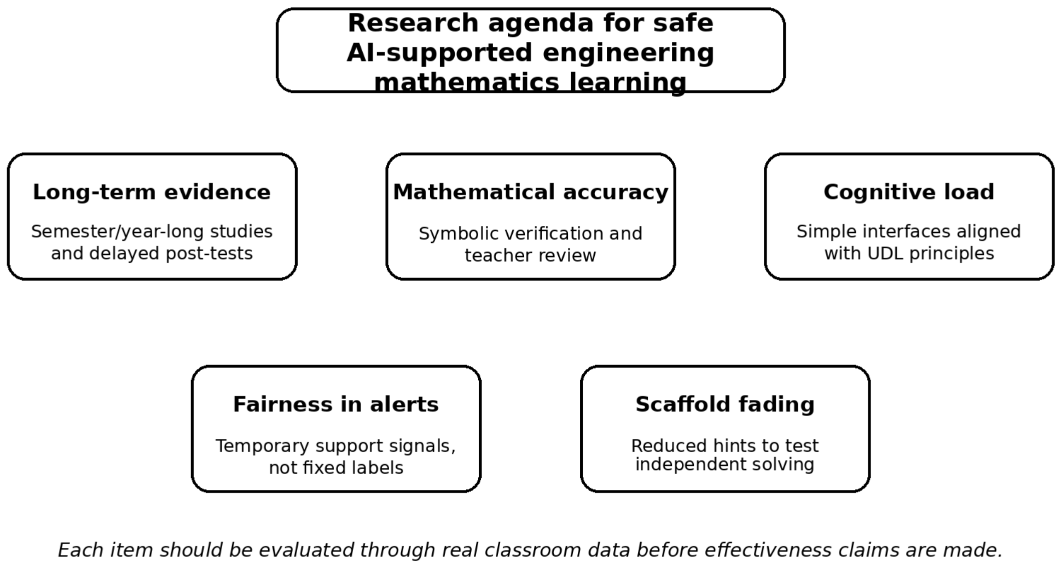

Fig. 2. Research agenda for safe and inclusive AI-supported engineering mathematics learning. The agenda emphasizes evidence, verification, cognitive-load management, fairness, and scaffold fading.

6. Proposed Conceptual Framework

The proposed framework contains six interacting layers. First, a multimodal input layer allows students to express mathematical reasoning through typed text, speech, tablet handwriting, selected diagrams, or structured formula entry. Second, a diagnostic assessment layer estimates prerequisite knowledge and identifies repeated error patterns. Third, an adaptive sequencing layer selects tasks so that prerequisite gaps are addressed before full engineering problems are attempted. Fourth, a neuro-symbolic verification layer checks generated mathematical content through deterministic symbolic or computer-algebra procedures wherever possible, for example by using SymPy, Mathematica, MATLAB Symbolic Math Toolbox, or similar symbolic engines where institutionally available. Fifth, a scaffolded feedback layer provides hints, worked examples, and partial steps. Sixth, a student-facing and teacher-facing analytics layer summarizes progress, topics completed, areas for review, and sustained difficulties requiring human attention.

The layers operate sequentially but with feedback loops: (1) learner input is collected; (2) diagnostic assessment estimates prerequisite gaps and error patterns; (3) if gaps are detected, adaptive sequencing selects foundational tasks before advancing to engineering problems; (4) all generated mathematical content is checked through the neuro-symbolic verification layer;

(5) scaffolded hints are delivered only after verification; and (6) the dashboard summarizes progress and flags sustained difficulty for teacher review. This architecture keeps the teacher in the loop while still allowing individualized practice. Scaffold fading is a central design rule. It follows a graduated release model: (a) demonstration, where the AI provides fully worked solutions with explanations; (b) guided practice, where students solve with hints and step-level feedback; (c) independent practice, where hints are progressively reduced; and (d) assessment, where no AI assistance is given. The pace of fading should be individualized based on diagnostic data, but the objective should be independent engineering problem solving, not permanent dependence on AI.

7. Comparison with Existing Frameworks

Traditional ITS architectures generally include a domain model, learner model, tutoring model, and interface model. The proposed framework builds on that tradition but emphasizes three additional concerns for engineering mathematics: mathematical verification of generated content, explicit scaffold fading, and teacher-interpretable analytics. Compared with broad AI-in-education frameworks such as the discussion of AI promises and implications by Holmes, Bialik, and Fadel [12], this paper narrows the focus to mathematical components embedded in engineering subjects and to learners who require additional support. The contribution is therefore not a new claim that AI improves learning by itself; it is a practical design synthesis for safer implementation in a specific engineering-education context.

8. Suggested Classroom Implementation

Table 2 provides a possible implementation sequence for an engineering mathematics support activity. It is intended as a planning template and not as a validated intervention protocol.

Phase	Suggested activity	Evidence collected	Teacher role
Week 1	Diagnostic quiz on prerequisites such as algebra, functions, trigonometry, and basic calculus	Error patterns, time on task, confidence ratings	Explain that alerts are support signals, not labels
Weeks 2-3	AI-supported prerequisite repair using short worked examples and micro-practice	Completion, repeated errors, hint use	Review difficult items and provide short mini-lessons
Weeks 4-5	Engineering-linked mathematical problems with verified step feedback	Intermediate steps, misconceptions, units/notation errors	Connect procedures with physical meaning
Weeks 6-7	Scaffold fading: fewer hints, more independent practice	Reduced hint use, accuracy without assistance	Monitor whether students can work independently
Week 8	Low-stakes assessment without AI assistance and reflective feedback	Independent solving performance and student perception	Decide future support and revise tasks

Table 2. Example implementation sequence for AI-supported engineering mathematics practice. The sequence is adaptable and should be validated before institutional adoption.

Institutions with shorter terms, modular courses, or 10-week quarters may compress diagnostic and practice phases or integrate AI support throughout the course rather than as a discrete intervention. The important requirement is not the exact number of weeks but the sequence: diagnosis, prerequisite repair, verified practice, scaffold fading, and teacher review.

9. Ethical and Practical Considerations

The system should not display the label 'slow learner' to students or use it as a permanent classification. Alerts should be treated as temporary indicators for support. Student data should be minimized, protected, and used only for educational purposes. Teachers should be able to override AI recommendations, and students should be told when AI is being used to generate hints or feedback.

Generated explanations should not be accepted as mathematically correct unless verified. For high-stakes concepts, the AI tutor should either use a trusted symbolic engine or computer algebra system, apply rule-based checks, or route uncertain outputs to teacher review. A confident but wrong derivation is more harmful for a struggling learner than no AI support at all.

Generative AI models may also reflect cultural or linguistic biases that affect students from non-Western educational backgrounds or students for whom English is an additional language. Engineering mathematics instruction should include examples and contexts relevant to diverse student populations, and AI-generated content should be reviewed for cultural inclusivity, linguistic clarity, and accessibility. These safeguards are consistent with wider trustworthy-AI policy directions, including the OECD AI Principles and the European Union AI Act's risk-based approach to AI systems used in education and vocational training [13], [14].

10. Future Research Directions

Future research should move from conceptual design to classroom validation. Important questions include: whether AI-supported prerequisite repair improves independent performance across multiple engineering courses; how different scaffold-fading strategies compare; what balance between automated feedback and teacher intervention is optimal; how students perceive AI tutors in high-stakes engineering contexts; and whether analytics-based alerts reduce or reinforce inequity. Longitudinal studies should include delayed post-tests and assessments without AI support so that independent competence can be measured.

11. Limitations

This paper is limited by design. It is a narrative review and conceptual proposal, not an empirical intervention study. It does not claim that the proposed framework improves marks, retention, or pass rates. The implementation sequence and framework should be tested using real student data, ethical approval where required, and transparent reporting of sample characteristics, learning outcomes, and limitations.

The term 'students requiring additional learning support' is preferred over fixed deficit labels. Future studies should define inclusion criteria transparently and avoid stigmatizing students.

12. Conclusion

AI can support the teaching of mathematical components in engineering subjects when it is designed as a supervised, inclusive, and verifiable learning aid. Intelligent tutoring systems and knowledge tracing can support diagnosis and adaptive practice; cognitive-load theory and UDL can guide accessible design; learning analytics can provide early support signals; and generative AI can offer conversational scaffolding when its output is carefully verified. For students requiring additional learning support, the central goal should be not continuous dependence on AI but a gradual transition toward independent mathematical reasoning in engineering contexts.

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