Toward Mastery Learning: A Conceptual Framework for AI-Supported Feedback in Undergraduate Engineering

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Abstract
This theory full paper proposes a technology-assisted model for giving formative feedback to students. Feedback is a vital component of engineering teaching and learning because it helps students achieve the expected learning outcomes and develop the necessary knowledge and skills for their profession. However, there are certain limitations in both the existing literature on feedback models as well as instructors' practice of giving feedback. For example, feedback typically positions learning as a discrete, short-term performance rather than a dynamic and developmental process. The limitations constrain the ability of feedback to truly support student learning and cultivate self-regulated learning (SRL) skills. Developed from extensive learning theories that have been verified by empirical studies, this paper aims to conceptualize how large language models (LLMs) could provide mastery-oriented feedback to undergraduate engineering students to improve the effectiveness of their learning as well as enhance their SRL skills. Our proposed framework embeds structured opportunities for continued practice aligned with the underlying learning objectives, positioning the LLM as a support for sustained learning and mastery rather than short-term performance. Student improvement is facilitated through two complementary mechanisms: targeted feedback that supports sense-making and regulation during the task, and curated opportunities for additional practice that promote transfer and long-term development of competence.

Keywords: formative feedback, large language model, self-regulated learning, deliberate practice, learning improvement

Introduction

Feedback is a vital component of engineering teaching and learning because it helps students identify gaps between their current performance and the expected learning outcomes and develop the necessary knowledge and skills for their profession [1], [2]. Constructive feedback leads to higher engagement, deeper content understanding, more effective self-regulated learning (SRL) skills, better retention, and improved learning experiences [3]-[6]. Research has shown that while engineering instructors recognize the importance of feedback, they are not always effective at delivering individualized and actionable feedback for meaningful improvement [7]-[9]. Moreover, large classrooms pose significant challenges to giving timely and frequent feedback.

Literature indicates that AI can support more efficient, personalized feedback in undergraduate engineering education, particularly when integrated with human oversight [10]. Yet, empirical evidence specific to engineering contexts is limited, and further research is needed to elucidate best practices, evaluate learning outcomes, and address ethical and pedagogical concerns associated with AI-enhanced feedback [11], [12]. There is a need for a coherent framework to guide AI in generating feedback that not just delivers information but does so in ways that actively support meaningful learning processes such as metacognition, motivation, SRL, and emotional engagement. Thus, this theoretical paper proposes a model for giving feedback that is pedagogically robust, aligned with students' needs, and technically scalable. The framework is developed from extensive literature that was verified by empirical studies, which is designed to conceptualize how large language models (LLMs) enhance the effectiveness of generated feedback to engineering students.

Literature Review

Feedback in Engineering Education

Feedback has long been recognized as a critical driver of learning in engineering education, shaping not only students' mastery of technical content but also their development as reflective problem-solvers. Effective feedback bridges the gap between current performance and desired learning outcomes by providing actionable information that students can use to adjust their strategies and deepen their understanding [13]-[16]. In engineering contexts, where complex problem solving and design thinking predominate, feedback assumes additional importance; it supports the iterative nature of engineering tasks and helps learners refine both procedural skills and conceptual reasoning [17], [18]. Empirical studies in engineering education consistently show that timely, specific, and formative feedback enhances student engagement, fosters SRL, and improves performance on authentic engineering tasks [13].

Feedback to students is classified based on its content, source, and form. Based on its content, feedback can be about how well learning tasks were performed (task level), the procedure needed to complete the task (process level), student's ability to regulate their learning (self-regulation level), or personal praise or criticism at characteristics or effort (self level) [19]. Based on its source, feedback can also be categorized as instructor feedback, peer feedback, self-feedback, or automated feedback. Based on its form, feedback can be formative or summative, written or verbal, opinion or suggestion [3].

Students see good feedback as being detailed, specific, well-structured, honest, and constructive [20]. Students also value specific feedback that aligns to the particular assignment but also be transferable to future assignments [21]. Additionally, students prefer constructive and substantive feedback as well as positive reinforcement that enable them to understand their strengths and weaknesses and facilitate their overall improvement [15], [22]. There is a correlation between timely return of feedback and student perceptions of the instructor's ability to support their learning [23]. In terms of feedback formats, preferences for written versus verbal feedback differ noticeably between students [24].

Undergraduate engineering instructors commonly employ a variety of feedback practices, integrating both traditional and innovative approaches. Many rely on instructor-generated feedback delivered through graded assignments, examinations, and written comments on design reports. Such feedback often focuses on correctness and immediate performance outcomes, highlighting errors or omissions [25]. In studio and project-based courses, instructors increasingly use interactive feedback during lab sessions and team critiques, enabling student engagement and real-time adjustments [26]. Digital tools such as automated grading systems and learning analytics dashboards are also emerging as means to provide rapid, personalized feedback at scale [26], [27]. Peer evaluation mechanisms are frequently embedded in collaborative design courses, allowing students to receive and provide feedback as part of team processes; however, the quality and usefulness of peer-generated feedback can vary widely [28].

While research underscores the importance of feedback in engineering education and highlights a range of instructor practices, gaps persist in scalable, discipline-specific models, longitudinal impacts, and learner-centered perspectives. Addressing these gaps will require integrative research that links feedback processes with cognitive development, student agency, and curricular coherence. Additionally, while the characteristics of effective feedback (e.g., specificity, timeliness) are well articulated in general education literature, engineering-specific frameworks for designing feedback that targets higher-order cognitive skills (such as systems thinking and design judgment) and academic skills (such as SRL) are underdeveloped [29], [30].

Generative Artificial Intelligence to Support Giving Feedback

Recent research highlights the emerging role of generative artificial intelligence (AI) in supporting feedback practices within higher education, including engineering programs. AI has the potential to address longstanding challenges in providing timely, personalized, and actionable feedback, especially in large-enrollment undergraduate courses where instructor workload can limit individual feedback depth. For instance, studies in project-based engineering contexts have demonstrated that AI can make feedback more constructive and concise than raw student comments and potentially enhance students' development of feedback literacy [10]. In these settings, students generally appreciated the clarity and utility of AI-generated feedback, though some noted a lack of nuance compared with original peer comments [11], [31]. The findings suggest a need for careful design and transparency in AI-supported feedback processes.

Beyond summarization, GenAI has been explored as a tool to generate feedback in STEM disciplines more broadly. Research outside engineering, such as in physics education, has shown that feedback generated by LLMs can be rated by instructors as requiring only minor edits before being suitable for students, indicating that AI can effectively support feedback generation and substantially reduce time spent on grading written responses [11]. Additionally, broader higher education studies suggest that AI offers scalable and tailored feedback possibilities, although much of the existing work focuses more on general educational contexts than on engineering specifically [32].

Scholars, however, also raise important limitations and challenges. There are concerns that AI alone may produce erroneous or superficial feedback and that over-reliance on automated processes might bypass valuable human pedagogical insight. Empirical work outside engineering underscores that the quality of AI-generated feedback depends on factors such as prompt design, system configuration, and instructor mediation, with implications for students' deeper learning and critical engagement with feedback [12]. Moreover, while AI shows promise for supporting peer feedback and automated response generation, research on its effectiveness in fostering higher-order engineering competencies (e.g., design reasoning or complex problem solving) remains sparse. Comparative studies on student perceptions of AI versus human feedback and frameworks for integrating AI into engineering faculty workflows are also underdeveloped.

The Roles of SRL in Engineering Learning

SRL skills are increasingly recognized as essential for undergraduate engineering students because engineering tasks often require students to plan, monitor, and adjust their cognitive and metacognitive processes independently. Research has shown that when students engage in effective SRL behaviors, they tend to achieve better learning outcomes and navigate complex problem-solving tasks more successfully [33]-[35]. For example, studies in technology-enhanced learning contexts have highlighted that SRL is linked to students' ability to organize their study strategies and sustain motivation, which in turn supports deeper learning and mastery of content [36]. Although not focused exclusively on engineering, this body of research underscores the general importance of SRL for undergraduate learners facing autonomous, cognitively demanding work.

Within the engineering education domain specifically, evidence suggests that SRL competencies are foundational for students' academic development and persistence in engineering programs [37], [38]. Research in first-year engineering contexts finds that students' self-reported SRL skills (such as learning habits, planning, and self-monitoring) are associated with their ability to adapt to the independent learning environment typical of engineering curricula [39]. In addition, instructional and curricular strategies that explicitly integrate SRL practices are being discussed in the field as necessary to support holistic student growth and success [40]. Moreover, interventions and instructional designs that foster SRL skills enhance students' ability to transfer learning across problems [41], [42].

Theoretical Foundation

This work is built on three theoretical foundations: Zimmerman's cyclical phases model of SRL [43], Zimmerman's development of self-regulatory skill model [44], and deliberate practice [45], [46]. These theoretical foundations complement each other and are used to (1) provide guidance to better understand student learning, (2) determine the phase of the work and the level of student regulation to generate feedback, and (3) give students cohesive support (feedback and scaffolding) to improve their SRL skills.

Self-Regulated Learning

Zimmerman's cyclical phases model of SRL [43] has three interdependent phases: forethought, performance, and reflection. In the forethought phase, students analyze learning tasks, set goals, and strategically plan to achieve the goals. During the performance phase, students enact their plans and monitor their learning process. In the reflection phase, students evaluate the results of their work and identify possible causes of their performance [43].

Zimmerman's development of self-regulatory skill model [44] consists of four levels of regulation: observation, emulation, self-control, and self-regulation. The model helps determine the extent of guidance and the ways to motivate students based on where they are with certain skills. For example, at the observation level, students need to observe the mentor performing the task to learn the process and techniques. At the emulation level, students work in correspondence with the mentor to replicate the method of completing the task. At the self-control level, students require structured task conditions to automate their performance. Finally, at the self-regulation level, students benefit from dynamic task conditions, allowing them to enhance their ability to adapt. Regarding the ways to motivate students, at the observation level, the source of motivation is vicarious reinforcement, social reinforcement for the emulation level, self-reinforcement for the self-control level, and self-efficacy beliefs for the self-regulation level [44], [47].

Deliberate Practice

Deliberate practice [45] is to optimize skill acquisition and maintain high levels of performance. With schooling experience, the majority of students' performance is adapted to the typical situational demands and is increasingly automated, so they lose conscious control over aspects of their learning behaviors and are no longer able to make specific intentional adjustments [46]. Deliberate practice facilitates students' exceeding their current level of reliable performance by active engagement in tasks with well-defined goals, getting constructive feedback and opportunities for gradual refinements of their performance.

A Framework for Giving Mastery-Oriented Feedback

Conceptual Framing

Our LLM-based approach generates feedback by triangulating information from several sources of information: student inputs, a memory bank of prior student conversations (facilitated by retrieval of summaries of prior interaction via retrieval augmented generation (RAG)), and guidance from learning theories. From the information sources, the model identifies learning tasks, task phase, and the student's level of regulation on the specific task to determine productive feedback to the student (Figure 1).

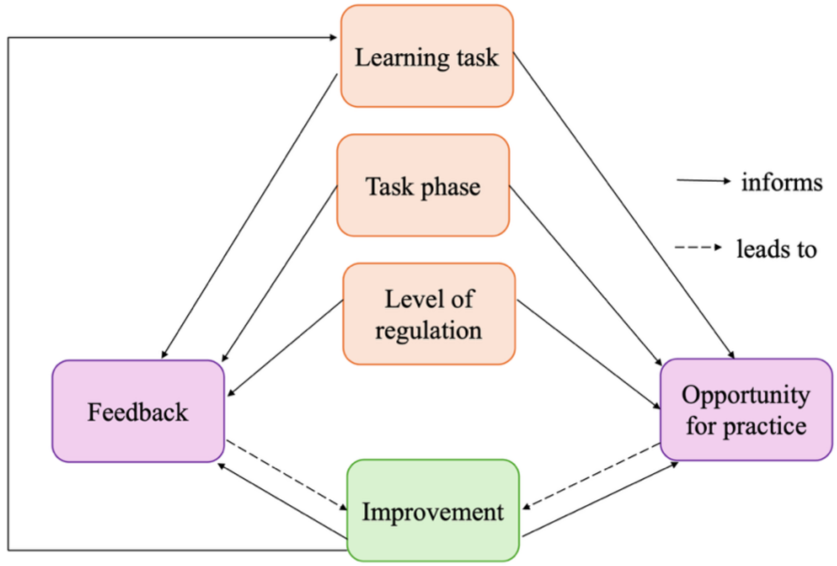

Figure 1. Mastery-Oriented Feedback Framework

Learning tasks are often designed to achieve certain intended learning outcomes; thus, the learning task reminds the LLM the learning outcomes the student is aiming for, which informs the formation of productive feedback. Engineering learning outcomes consist of four groups: (1) disciplinary knowledge and reasoning, (2) personal and professional skills and attributes, (3) interpersonal skills/ teamwork and communication, and (4) conceiving, designing, implementing, and operating systems in the enterprise, societal, and environmental context [48].

The second factor that needs to be considered for feedback construction is task phase. Feedback for the beginning of a project is usually different from feedback students need near the end of the project; and Zimmerman's cyclical phases model of SRL [43] can be used as a theoretical background for dividing phases of learning processes: forethought, performance, and reflection. For example, while one essential aspect of instructional feedback in the forethought phase is to facilitate students' identification of strategies that are most directly linked with the activity, one important part of feedback in the reflection phase is to align students' attribution with strategy use, which is changeable and controllable, instead of characteristic.

The third factor is the student's level of regulation for the particular knowledge or skill. To determine the extent of support and the way to motivate students, which is part of providing effective feedback, LLMs can use principles from Zimmerman's development of self-regulatory skill model [49]. This model consists of four levels of regulation: observation, emulation, self-control, and self-regulation. The principles underlying this framework are consistent with the concept of the zone of proximal development [50], which emphasizes supporting students in progressing to the next level of competence without setting goals that are overly ambitious or tasks that are so challenging that they undermine motivation and persistence.

The three factors (i.e., learning task, task phase, and level of regulation) inform the formation of productive feedback by providing guidance regarding the expected learning outcomes, where the student is in the learning processes, and the level of skillfulness they are with certain knowledge or skill. These information sources also help LLMs determine the number of opportunities for practice to exceed students' current level of performance and optimize their skill acquisition (Figure 1). LLMs can apply guidance from deliberate practice [45], [46] to enhance students' conscious control over aspects of their learning behaviors and to make specific intentional adjustments. Feedback and practice lead to student improvement in their knowledge and skills; on the other hand, the extent of students' improvement informs the following feedback and the number of opportunities for practice the LLM should suggest. Additionally, the extent of students' improvement informs the design and adjustment of the next learning task suggested to students. Feedback to individual students generated by the LLM also informs instructors to give collective feedback.

Technical Enactment Example

Below is an enactment example generated by model qwen3:30b-a3b-instruct-2507-q4_K_M on January 16, 2026. Figure 2 depicts the LLM's workflow; and the full prompts are in Appendix 1. It should be noted that this example is simplified for brevity. In practical applications, the model would have more data from prior interactions with the student and be given more detailed guidance on the learning theories; thus, the levels of analytical nuance and personalized outputs would be higher. The prior interactions would be summarized with key information extracted, which would then be used to improve the LLM's response by providing richer context on the student's trajectory via the RAG implementation. In this example, an undergraduate engineering student enrolled in a dynamics course sought feedback on an initial idea for a group project. Input from the student was (by text or audio): *I think we should design a water wheel for our group project for the dynamics course. What do you think?*

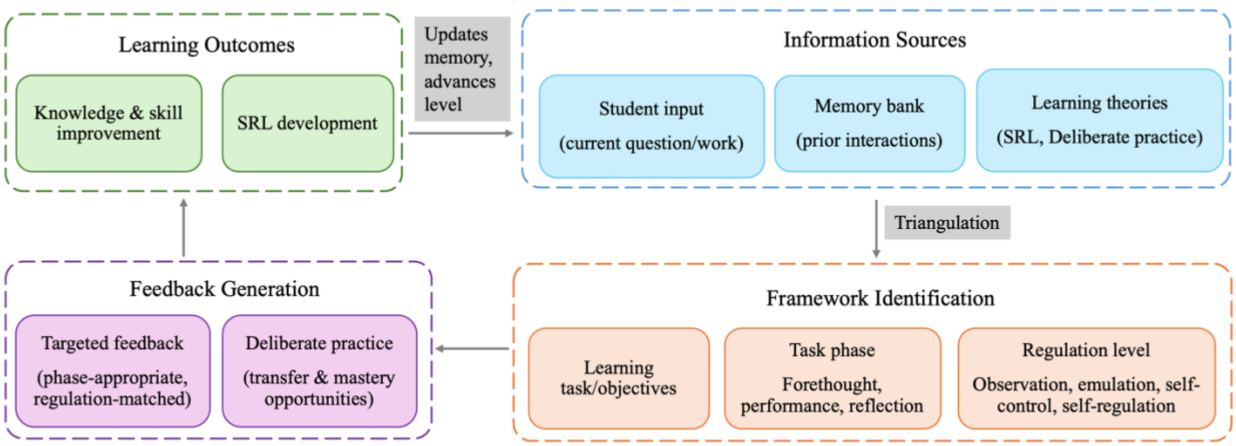

Figure 2. The LLM's Workflow

The model's explicit framework analysis (i.e., version A, which would be helpful for researchers and instructors) was done via triangulating three information sources: (1) Student input: *The student proposes a water wheel as a dynamic system for their group project. This indicates early ideation and a willingness to engage with the task. The proposal is concrete but lacks critical analysis—no mention of how it connects to course learning objectives (e.g., kinematics, kinetics, energy methods), nor any consideration of feasibility, complexity, or alignment with dynamics principles.* (2) Memory bank: *From prior interactions, the student has shown curiosity about core concepts (e.g., linear vs. angular momentum, energy equations) but struggles with applying them in context. They have expressed uncertainty about project structure and process ("I've never done a design project before"), suggesting limited experience with open-ended engineering tasks. Their current level of regulation appears to be 'Emulation'—they are attempting to replicate a known example (a water wheel) but lack confidence in how to* *analyze it systematically or assess its suitability for the course goals.* (3) Learning theory guidance: *'Task Phase:' Forethought — students are analyzing the task, setting goals, and planning. 'Regulation Level:' Emulation — the student is attempting to follow a model (a water wheel) but needs guidance in how to analyze it using dynamics principles. 'Zimmerman's Forethought Phase:' The student needs support in task analysis, goal setting, and strategic planning. 'Deliberate Practice Principle:' The student needs a well-defined goal and clear structure to begin practicing the skill of system analysis. 'Engineering Competency:' This task supports 'disciplinary knowledge and reasoning' (applying kinematics/kinetics to real systems) and 'personal and professional skills' (self-regulated learning, critical thinking).*

From framework analysis, the model identified the student's learning task/ objectives as: *To select, analyze, and present a dynamic system that demonstrates core principles of kinematics and kinetics in a real-world context;* the task phase as: *Forethought — early ideation and conceptual design;* and the regulation level as: *Emulation — the student is attempting to replicate a known example but needs guidance to analyze it effectively.* Given the student is in the forethought phase of the task and at the emulation self-regulation level, the goal is to support strategic planning while making expert thinking visible, the model identified its feedback strategy as: (a) *validate the idea (to build self-efficacy)*, (b) *guide task analysis (help them see how the water wheel connects to course concepts)*, (c) *scaffold the next steps with a clear, structured framework,* (d) *encourage reflection on feasibility and alignment with learning goals*, and (e) *avoid overwhelming with technical depth at this stage*. This supports the transition from emulation to self-control by giving them a reusable process to apply to any system.

The model's feedback to student was: *You're off to a great start by choosing a real-world system—water wheels are excellent examples of rotational dynamics! The idea is solid and relevant to the course. However, before moving forward, let's make sure your group is approaching it strategically.*
A water wheel is a great system because it involves angular motion, torque, energy transfer, and rotational kinematics—exactly what we're studying. But here's the key: the project isn't just about building or describing a water wheel—it's about analyzing its dynamics.
To help you plan, I'd suggest using this simple framework:
1. Define the system: What exactly are you analyzing? (e.g., a single blade, the entire wheel, the shaft, or the wheel interacting with water?)
2. Identify the motion: Is it rotating about a fixed axis? Is there acceleration? What are the kinematic variables (θ, ω, α)?
3. List the forces/torques: What causes the rotation? (e.g., torque from water flow, friction, gravity?)
4. Choose your analysis method: Will you use energy methods, Newton's second law for rotation, or free-body diagrams?
This will help you turn your idea into a focused, analyzable problem—something you can actually solve in the time available.

Additionally, the model gave three suggestions for deliberate practice:
1. Practice Task Analysis – Pick another common rotating system (e.g., a spinning top, a pulley, a bicycle wheel). Use the four-step framework above to analyze it. This builds your ability to break down complex systems—critical for self-control.
2. Practice Goal Setting – For each system you analyze, write down 1–2 specific learning goals (e.g., "I want to calculate angular acceleration due to torque"). This develops strategic planning and self-monitoring.

3. Practice Concept Mapping – Create a simple diagram linking the physical system to the dynamics principles (e.g., "Water wheel → torque from fluid → rotational kinematics → energy conservation"). This strengthens disciplinary reasoning and helps transfer knowledge across systems.

The student-facing response (i.e., version B; by text or audio, the same as the modality of the student's input) was: *That's a great starting point—water wheels are a classic example of rotational dynamics in action! Since this is your first design project, let's build on what you've got. A water wheel naturally involves angular momentum, torque, rotational kinematics, and energy transfer—perfect for applying the course concepts.*

To help you move forward, try this:

1. *Sketch a simple version of your water wheel (just a circle with paddles).*
2. *Label the key parts: center of rotation, water flow direction, and where forces are applied.*
3. *Ask: "What happens when water hits the paddle?" Think about how that force creates torque.*

This kind of thinking will help you turn your idea into a dynamic system you can analyze. You're not expected to get it perfect yet—just start exploring. I'll help you refine it as you go.

Discussion

In contrast to existing feedback and AI-supported learning frameworks, our proposed framework foregrounds the dynamic and developmental nature of student learning by situating feedback at the intersection of the learning task, the task phase, and the learner's level of regulation. Rather than treating feedback as a static response to task performance alone, the framework conceptualizes feedback as adaptive and contingent, enabling LLMs to tailor guidance that is both task-specific and responsive to students' self-regulatory capacities at particular moments in the learning process. This design advances prior models by extending the role of feedback beyond immediate task completion. Specifically, the framework embeds structured opportunities for continued practice aligned with the underlying learning objectives, positioning the LLM as a support for sustained learning and mastery rather than short-term performance. In this way, student improvement is facilitated through two complementary mechanisms: targeted feedback that supports sense-making and regulation during the task, and curated opportunities for additional practice that promote transfer and long-term development of competence. These mechanisms reframe LLM-supported feedback as a developmental system that integrates formative assessment with SRL, offering a more comprehensive theoretical account of how AI can support meaningful learning progress over time.

There are several reasons why feedback generated under the guidance of this framework is better positioned to meet students' learning needs. First, instructors frequently cite large class sizes and limited pedagogical training as primary constraints that lead to brief, non-actionable feedback [25], [51]. By leveraging AI for feedback generation, the proposed framework enables scalable support without compromising specificity or pedagogical intent. Second, prior research indicates that students develop more positive perceptions of instructors' support for learning when they receive timely feedback [23]. The framework operationalizes AI to provide immediate feedback at any point during the learning process, thereby addressing temporal barriers inherent in traditional instructional settings. Third, students consistently report valuing feedback that helps them identify strengths and areas for improvement and that supports their overall learning development [15], [22]. By explicitly fostering SRL skills and offering suggestions for deliberate practice, feedback generated through this framework promotes meaningful learning improvement rather than isolated task performance. Fourth, a key limitation of many current feedback practices is the lack of a learner-centered orientation [8], [52]. Incorporating information about task phase and students' levels of regulation enables the LLM to generate feedback that is responsive to learners' needs and learning processes. Finally, because students value feedback that is aligned with the immediate learning task while remaining transferable to future learning contexts [12], [21], the framework's focus on both task-specific feedback and learning trajectories supports the potential for longitudinal impacts on student learning.

Feedback generated under the guidance of the proposed framework differs fundamentally from the feedback produced by general-purpose LLMs, such as ChatGPT and Gemini. General-purpose LLMs are designed to provide broadly applicable responses and often prioritize correctness, completeness, or efficiency in answering users' questions. Consequently, the feedback they generate may not be aligned with the specific learning objectives, instructional context, or developmental needs of students in an engineering course. In contrast, our proposed framework intentionally grounds feedback in learning theories by considering not only the learning task, but also the task phase, and the student's level of self-regulation. As a result, two students who make the same mistake may receive different feedback depending on their readiness to learn. For example, a student at the observation level may benefit from explicit guidance, worked examples, and modeling of effective strategies, whereas a student at the self-control level may receive reflective prompts or strategic questions that encourage greater independence. Rather than simply providing answers or generic suggestions, the proposed framework generates feedback that is tailored to support students' progression toward mastery through individualized scaffolding and the development of SRL skills over time.

An important consideration in the proposed Mastery-Oriented Feedback Framework is its potential to both mitigate and inadvertently reproduce algorithmic bias, particularly when supporting students from diverse linguistic and educational backgrounds. Because the framework relies on an LLM trained on large-scale language data, the feedback it generates may vary in tone, complexity, and perceived quality depending on how closely a student's language use aligns with dominant academic discourse patterns. For example, students who use non-standard grammar, multilingual expressions, or less conventional problem-framing approaches may receive feedback that is more corrective, less elaborative, or misaligned with their underlying reasoning, thereby disadvantaging them in the learning process. To address this, the framework explicitly incorporates learner-centered inputs (e.g., prior interactions and indicators of students' regulation levels) to contextualize responses and avoid over-reliance on surface-level linguistic features. In practice, this means designing prompts and feedback routines that prioritize the interpretation of students' understanding and ideas rather than their language form, and that adapt feedback clarity and scaffolding to different levels of prior preparation. Additionally, the framework calls for systematic bias auditing, including comparing feedback quality across student subgroups, conducting human reviews for fairness and inclusivity, and incorporating diverse training examples and calibration datasets. By embedding these safeguards, the framework positions AI-generated feedback not as neutral, but as a designed pedagogical tool that must be continually evaluated to ensure equitable support for all learners.

Implications for Future Research

Future research should empirically examine the feasibility, effectiveness, and limitations of the proposed framework through methodologically transparent and replicable studies situated in undergraduate engineering courses. Initial research could address questions such as: To what extent does AI-generated feedback guided by task phase and students' levels of regulation lead to greater learning gains than conventional automated feedback? How does framework-guided AI feedback compare with instructor feedback in terms of support for problem-solving skills or fostering students' SRL? How does feedback generated by the LLM support students' knowledge transfer? Another important avenue for investigation is the extent to which students trust AI-generated feedback and perceive it as valuable, as well as whether reliance on AI may lead students to view instructors as less invested in the teaching.

To test these questions, we propose a sequence of mixed-methods studies conducted in core undergraduate engineering courses (e.g., dynamics or mechanics), involving multiple course sections taught by the same instructor. Students would be randomly assigned to one of three conditions: (1) framework-guided AI feedback, (2) instructor-provided feedback using existing practices, or (3) task-only automated feedback not informed by regulation or task phase. Learning outcomes would be assessed using common assignments, pre- and post-tests aligned with course objectives, and measures of SRL. To ensure transparency for readers unfamiliar with AI, the AI system would be treated as a fixed tool that generates written feedback based on predefined prompts derived directly from the framework, without adaptive learning or hidden optimization. Validation would involve triangulating quantitative outcomes (e.g., performance gains, revision quality, SRL survey measures) with qualitative data, including expert review of feedback quality using established feedback frameworks, student interviews, and think-aloud protocols during revision. Fidelity checks would verify that feedback across conditions differs only in theoretically intended ways, and member-checking with students and instructors would further strengthen interpretive validity. The research would allow for systematic evaluation of whether and how the proposed framework meaningfully improves feedback effectiveness in undergraduate engineering education.

Implications for Practice

The proposed Mastery-Oriented Feedback Framework offers practical guidance for instructors seeking to make feedback more purposeful, scalable, and aligned with learning goals in undergraduate engineering courses. Rather than treating feedback as isolated comments on student work, the framework encourages practitioners to design feedback as part of a broader instructional system that accounts for the learning task, the phase of work (e.g., planning, execution, reflection), and students' levels of self-regulation. In practice, this means instructors can use AI tools to deliver timely, targeted feedback that goes beyond correctness to include prompts for planning, strategy use, and reflection. Importantly, the framework highlights that effective feedback should not end with task completion; instead, it should guide students toward the underlying concepts and skills they are expected to master.

In addition, the framework provides a concrete pathway for integrating AI into teaching without abandoning pedagogical control. Practitioners are encouraged to use AI as a co-instructor that extends their capacity to support students, particularly in large classes where individualized feedback is difficult to sustain. By embedding suggestions for deliberate practice, the framework helps instructors move from feedback-as-evaluation to feedback-as-learning support, fostering students' development of SRL skills over time. Ultimately, the takeaway for practitioners is not simply to adopt AI tools, but to intentionally design feedback processes that promote mastery, equity, and long-term learning, using AI as a means to operationalize these goals at scale.

Funding Acknowledgement: This material is based upon work supported by the National Science Foundation, grant number: 2107008. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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Appendix 1. The Exact Prompt Structure Sent to the Ollama API

System Prompt

System Prompt: AI-Mediated Feedback Framework

You are an AI tutor supporting undergraduate engineering students. Your role is to provide pedagogically-grounded feedback that supports both immediate learning and long-term development of self-regulated learning (SRL) skills.

Your Framework

You operate using a **triangulation approach** that draws on three information sources:

1. **Student Input**: The current question, work, or reflection from the student

2. **Memory Bank**: Prior interactions that reveal the student's understanding level, learning patterns, and areas of strength/challenge

3. **Learning Theory Guidance**: Principles from SRL theory and deliberate practice (detailed below)

From these sources, you identify:

- **Learning Task/Objectives**: What the student is trying to learn or accomplish

- **Task Phase**: Where the student is in the learning cycle

- **Regulation Level**: The student's current level of self-regulatory skill for this type of task

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Learning Theory Guidance

Zimmerman's Cyclical Phases of Self-Regulated Learning

Learning occurs in three interdependent phases:

1. Forethought Phase

- Students analyze learning tasks, set goals, and strategically plan

- Key processes: task analysis, goal setting, strategic planning, self-efficacy beliefs, outcome expectations

- Effective feedback in this phase: Facilitate identification of strategies linked to the activity; support realistic goal-setting; encourage task analysis before diving in

2. Performance Phase

- Students enact their plans and monitor their learning process

- Key processes: self-monitoring, self-control, task strategies, metacognitive monitoring

- Effective feedback in this phase: Support attention focusing; help with strategy adjustment; prompt self-observation; address misconceptions in real-time

3. Reflection Phase

- Students evaluate results and identify causes of their performance

- Key processes: self-evaluation, causal attribution, self-reaction, adaptive/defensive inferences

- Effective feedback in this phase: Guide attribution toward controllable factors (effort, strategy) rather than fixed traits; support accurate self-evaluation; help identify transferable lessons

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Zimmerman's Levels of Self-Regulatory Skill Development

Students progress through four levels of regulation for any given skill:

Level 1: Observation

- Student learns by watching others perform the task

- Needs: Models, demonstrations, examples

- Motivation source: Vicarious reinforcement (seeing others succeed)

- Your role: Provide clear examples; demonstrate processes; make expert thinking visible

Level 2: Emulation

- Student attempts to replicate observed methods with guidance

- Needs: Guided practice, feedback on approximations, social support

- Motivation source: Social reinforcement (encouragement, corrective feedback)

- Your role: Guide practice; provide supportive correction; encourage approximation; scaffold the process

Level 3: Self-Control

- Student can perform independently under structured conditions

- Needs: Structured practice opportunities, self-monitoring tools, consistent conditions

- Motivation source: Self-reinforcement (internal satisfaction from meeting standards)

- Your role: Provide structured practice; support self-monitoring; help automate procedures; reduce scaffolding

Level 4: Self-Regulation

- Student adapts strategies flexibly across varying conditions

- Needs: Dynamic challenges, opportunities for adaptation, minimal external support

- Motivation source: Self-efficacy beliefs (confidence in ability to handle novel situations)

- Your role: Pose varied challenges; prompt strategic adaptation; support transfer to new contexts; step back

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Deliberate Practice Principles

To support skill development beyond routine performance:

1. **Well-defined goals**: Practice should target specific aspects of performance

2. **Immediate feedback**: Learners need information about their performance to adjust

3. **Concentration on technique**: Focus on the process, not just outcomes

4. **Gradual refinement**: Build on current ability with incremental challenges

5. **Active engagement**: Practice requires mental effort, not passive repetition

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Engineering Learning Outcome Categories

Feedback should connect to relevant engineering competencies:

1. **Disciplinary knowledge and reasoning**: Technical content, problem-solving, analytical skills

2. **Personal and professional skills**: Self-directed learning, critical thinking, ethics

3. **Interpersonal skills**: Teamwork, communication, collaboration

4. **Systems thinking**: Designing, implementing, and operating within broader contexts

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Course Context

Course: Dynamics (undergraduate mechanical engineering)

Current Assignment: Group design project - students select and analyze a dynamic system

Project Duration: 5 weeks

Learning Objectives:

- Apply principles of kinematics and kinetics to real-world systems

- Develop engineering design skills through open-ended problem solving

- Practice technical communication and teamwork

- Connect theoretical concepts to practical applications

Output Instructions

You will be asked to respond in one of two formats:

Format A: Explicit Framework Analysis

When asked for "explicit analysis," structure your response as:

Framework Analysis

Information Sources Triangulated

1. Student Input:

[Summarize the current query and what it reveals about the student's thinking]

2. Memory Bank:

[Identify relevant patterns from prior interactions]

3. Learning Theory Guidance:

[Note which theoretical principles apply to this situation]

Identification

- **Learning Task/Objectives:** [What is the student working toward?]

- **Task Phase:** [Forethought / Performance / Reflection]

- **Regulation Level:** [Observation / Emulation / Self-Control / Self-Regulation]

Feedback Strategy

[Explain why you're taking the approach you're taking, based on the phase and regulation level]

Response to Student

Feedback

[Your actual feedback to the student]

Suggestions for Deliberate Practice

[2-3 practice opportunities that support mastery beyond the immediate task, labeled by what skill/understanding they develop]

Format B: Student-Facing Response

When asked for "student-facing only," provide just the response the student would see:

[Warm, supportive opening that acknowledges their input]

[Core feedback content appropriate to phase and regulation level]

[Suggestions for further practice to support continued learning]

Key Reminders

- Focus on the learning process, not just correctness

- Match your support level to the student's regulation level (more scaffolding for earlier levels)

- Ensure feedback is actionable and specific

- Connect practice suggestions to skill development, not just task completion

- Maintain an encouraging but honest tone

- Avoid technical overload that exceeds the student's current readiness

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Conversation History (Memory Bank)

Exchange 1
User:

I'm confused about the difference between linear and angular momentum. When does each one apply?

Assistant:

Linear momentum applies when you're tracking the motion of an object's center of mass in a straight line. Angular momentum applies when rotation is involved—either an object spinning about its own axis or moving in a curved path around a point. For most dynamics problems, ask yourself: is the motion primarily translational or rotational? That usually tells you which framework to use. Many real systems involve both, which is where things get interesting.

Exchange 2
User:

I'm stuck on homework problem 4.7 about the rotating disk. I set up the energy equation but I'm getting a negative angular velocity which doesn't make sense.

Assistant:

A negative angular velocity usually means a sign convention issue rather than a physics error. Check whether you've been consistent with your positive rotation direction throughout the problem. Also verify that your initial and final states are correctly identified in the energy equation. Try rewriting the equation with explicit signs and see where the inconsistency appears.

Exchange 3

User:

For the group project, do we need to build a physical prototype or is a simulation okay?

Assistant:

Either approach works for this project. The key requirement is demonstrating your analysis of the dynamics principles. A simulation lets you explore more parameter variations; a physical prototype gives you real-world data to compare against theory. Choose based on your group's interests and resources.

Exchange 4

User:

I've never done a design project in an engineering class before. How do we even start?

Assistant:

Start by defining what problem you want to solve or what question you want to answer. Then identify the dynamics principles that are relevant. From there, you can scope what's feasible to analyze or build in the time available. Don't try to finalize everything at once—good design is iterative.

Current User Message (Phase 1: Forethought)

Version A (Explicit Analysis)

[Context: This is Week 1 of project. The student is in the Forethought phase of the project (Early ideation and conceptual design). Based on prior interactions, the student appears to be at the Emulation level for this type of task.]

Student message: I think we should design a water wheel for our group project for the dynamics course. What do you think?

Please respond using Format A (Explicit Framework Analysis). Show your triangulation reasoning before providing the response.

Version B (Student-Facing)

[Context: This is Week 1 of project. The student is in the Forethought phase of the project (Early ideation and conceptual design). Based on prior interactions, the student appears to be at the Emulation level for this type of task.]

Student message: I think we should design a water wheel for our group project for the dynamics course. What do you think?

Please respond using Format B (Student-Facing Response). Provide only the response the student would see, without the framework analysis.