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Scaffolding Cognitive Apprenticeship in Mechanics Education via Generative AI

Dr. Zubaer Hossain, Texas A&M University

Dr. Hossain received his PhD degree in Mechanical Engineering from the University of Illinois at Urbana-Champaign (UIUC). Prior to joining Texas A&M as an associate professor of instruction, he was an assistant professor at UD and served as a postdoctoral scholar at California Institute of Technology. He also worked as a visiting scientist at Lawrence Livermore National Laboratory and as a visiting scholar at Johns Hopkins University. His research and teaching interests include mechanics and physics of deformation and fracture in semiconductors, heterogeneous materials, and composites. He explores the role of material and structural anisotropy and asymmetry in controlling effective properties at multiple scales. Improving domestic students' success and participation in higher education and research drives his teaching and mentoring ambitions.

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Abstract

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Engineering students often struggle to synthesize interdependent mechanics concepts such as stress, strain, stiffness, and fatigue into coherent mental models that support design reasoning. This paper examines how Generative AI (GAI) dialogue can function as a cognitive apprenticeship scaffold for conceptual learning in undergraduate mechanics.

Grounded in theories of conceptual learning and cognitive apprenticeship, the study structures student–AI interaction around modeling, coaching, questioning, and reflective articulation rather than solution delivery. The intervention was implemented in a completed junior-level mechanical design course, where ChatGPT was deployed as a constrained conversational partner designed to prompt reasoning, surface assumptions, and require justification of analytical steps. To mitigate risks associated with AI hallucination and superficial correctness, the system was explicitly restricted from providing final numerical answers or authoritative claims, and students were required to validate all reasoning using governing equations, physical interpretation, and instructor-verified references.

AI-mediated dialogue was integrated with conventional instruction, JupyterLab-based computational notebooks, and paper-based assessments. Data sources include in-class transcripts of student–AI interactions, structured student reflections, and performance on midterm and final exams administered during the same term. Qualitative analysis indicates increased metacognitive awareness, more frequent articulation of relationships among mechanics variables, and improved integration of geometry, loading, and material behavior during design reasoning. Quantitative comparisons of exam responses with prior course offerings suggest improved conceptual coherence and error detection, providing short-term evidence of learning gains.

While long-term retention across subsequent courses has not yet been evaluated, the results demonstrate how GAI can support learning when embedded within a clearly defined pedagogical structure that emphasizes reasoning over answers.

1 Introduction

Undergraduate mechanics courses such as statics, solid mechanics, and machine design constitute a foundational pillar of mechanical engineering education, serving as the conceptual bridge between basic physics and professional design solutions that benefit society. These courses remain persistently challenging for students, not primarily because of mathematical difficulty, but because they must construct and coordinate multiple concepts into a coherent mental picture. Unlike many early engineering courses such as calculus and introductory programming that emphasize procedural fluency or algorithmic problem solving skills, mechanics demands relational reasoning across interacting physical phenomena, governing principles, competing design objectives, and internal force transfer mechanisms. Prior research has shown that students often develop fragmented knowledge structures in these foundational courses, demonstrating procedural competence without a corresponding ability to reason conceptually [1, 2].

In mechanics contexts, quantities such as stress, stiffness, strength, and stability emerge from the coupled interaction of geometry, material behavior, constraints, and loads. Expert engineers navigate these interdependencies fluently by recognizing governing mechanisms and tradeoffs, whereas novices frequently approach such analyses as isolated calculations applied sequentially. For instance, a change intended to improve strength may inadvertently degrade stiffness or trigger an instability; similarly, a geometric modification introduced for manufacturability may alter load transfer and governing failure modes. While experts synthesize these factors naturally, students are often introduced to underlying concepts in a linear fashion and assessed in isolation. As a result, students may demonstrate local competence in specific topics while lacking the integrative understanding necessary for design reasoning. This fragmentation elevates cognitive load and hinders their ability to both know and do in the ABET sense, ultimately constraining the development of genuine mastery [3–5].

Bolted connections provide a particularly revealing example of this challenge. Even relatively simple joints may simultaneously involve bearing stresses at bolt holes, net section tension, bolt shear, joint slip, plate bending, and out of plane buckling [6, 7]. Prior studies of student reasoning in mechanics indicate that such multi mechanism problems are especially prone to checklist based analysis, in which failure modes and factors of safety are evaluated independently rather than as interacting aspects of a single mechanical system. The governing behavior is rarely apparent a priori and depends critically on geometry, fastener layout, and load introduction. For students, this interdependence can be difficult to visualize and internalize at the metacognitive level. Consequently, students may correctly compute individual quantities while failing to develop an internalized understanding of why certain failure modes govern or how design decisions propagate through the system. This gap is significant because navigating such complexities is a routine requirement in industrial mechanical design practice.

These difficulties point to a deeper pedagogical issue: much of the knowledge required for competent mechanics based design is tacit and systemic. Traditional lectures, worked examples, and solution manuals often obscure the reasoning processes that experts use to identify dominant mechanisms, select appropriate models, and interpret results physically. Learning sciences research further suggests that activities requiring learners to generate explanations and engage in interactive dialogue produce deeper learning than passive or procedural engagement, particularly for complex conceptual material [2]. This limitation reflects a broader challenge in engineering education, where tacit expert knowledge is rarely externalized for learners despite its central role in professional practice [8, 9]. What students most need to learn—how to think like a mechanics informed designer—is precisely what is least visible in conventional instruction.

Cognitive apprenticeship offers a theoretically grounded framework for addressing this gap [10–12]. Rooted in situated learning theory, cognitive apprenticeship emphasizes making expert thinking explicit through modeling, coaching, scaffolding, articulation, and reflection within authentic tasks. Cognitive apprenticeship seeks to make expert thinking visible so that learners can appropriate disciplinary ways of reasoning rather than merely reproduce solutions. In the context of mechanics, this involves exposing how experts reason about load paths, justify simplifying assumptions, anticipate failure modes, and reconcile analytical predictions with physical intuition. However, implementing cognitive apprenticeship consistently in undergraduate mechanics courses is challenging, particularly in large-enrollment settings where opportunities for sustained, individualized dialogue are limited. Empirical studies have shown that sustained coaching and guided articulation are among the most impactful, but also the most resource-intensive, elements of cognitive apprenticeship implementations [13].

Recent advances in generative artificial intelligence present new possibilities for operationalizing cognitive apprenticeship at scale. Recent educational research suggests that AI-driven dialogue systems can support modeling, questioning, and reflection when designed as scaffolds rather than answer generators [14, 15]. When used intentionally, GAI can support interactive dialogue, adaptive questioning, and reflective prompts that mirror aspects of expert coaching. Importantly, the pedagogical value of GAI does not lie in answer generation or automation of problem solving, but in its capacity to scaffold reasoning, surface assumptions, and encourage students to articulate and test their understanding. Used poorly, such systems risk promoting superficial correctness or false confidence; used carefully, they offer a means to extend expert-like dialogue beyond the constraints of time and staffing.

This paper argues that generative AI, embedded within a principled cognitive apprenticeship framework, can support deeper conceptual learning in undergraduate mechanics. Through an empirical study situated in a junior level mechanical design course, we demonstrate how AI mediated dialogue can help students integrate strength, stiffness, and stability considerations in the analysis of bolted connections. By focusing on reasoning rather than answers and by anchoring AI interaction to established mechanics principles and independent assessment, this work contributes evidence based insight into how Generative AI (GAI) can function as a pedagogical collaborator in mechanics education rather than a substitute for expertise. In particular, this study aims to address two research questions:

(1) How does GAI operationalize cognitive apprenticeship in undergraduate mechanics across the dimensions of modeling, computing, analyzing, and reflection?

(2) What short term indicators of conceptual learning and reasoning quality are observed in student work when GAI is embedded as a scaffold rather than a solution generator?

The contributions of this paper are threefold. First, we present an implementable instructional design that integrates GAI as a constrained coaching partner within a multi constraint mechanics design task. Second, we provide a worked case study involving a gusset plate bolted connection that shows how GAI prompts can be sequenced to elicit expert like reasoning about load paths, governing mechanisms, and physically grounded interpretation. Third, we report short term evidence from student AI transcripts, structured reflections, and exam artifacts, including both qualitative indicators of reasoning and descriptive quantitative comparisons with prior course offerings.

2 Cognitive Apprenticeship in Mechanics Education

Cognitive apprenticeship frames learning as a process of guided participation in authentic disciplinary practices, with particular emphasis on making expert reasoning explicit and accessible to novices. In engineering mechanics, this perspective is especially salient because competence extends well beyond procedural manipulation of equations. Expert mechanics reasoning involves selecting appropriate idealizations, identifying governing mechanisms among competing possibilities, and interpreting analytical results in terms of physical behavior and design intent. These forms of knowledge are often tacit, developed through experience, and rarely articulated explicitly in traditional instruction.

The challenge is particularly acute in topics where strength, stiffness, and stability are tightly interdependent. In practical design problems, these concepts do not represent separate analytical checks, but intertwined dimensions of system behavior. A connection that is adequate in strength may fail to meet stiffness requirements or exhibit instability under service loads. Similarly, geometric modifications intended to improve buckling resistance may alter load paths and introduce localized stress concentrations. Expert engineers reason fluidly across these interdependencies, continuously evaluating tradeoffs and revisiting assumptions as the design evolves. Novice learners, by contrast, often approach mechanics analysis as a sequence of disconnected calculations, applying formulas without a coherent understanding of how individual results relate to the behavior of the overall system.

Cognitive apprenticeship directly addresses this gap by emphasizing modeling, coaching, scaffolding, articulation, reflection, and exploration within realistic problem contexts. Modeling in mechanics involves making visible how experts conceptualize load transfer, construct free-body diagrams, and decide which failure modes merit detailed analysis. Coaching and scaffolding support students as they attempt similar reasoning, providing prompts that guide attention to critical features without removing responsibility for decision-making. Importantly, scaffolding in mechanics must encourage students to reason about why a particular mechanism governs, rather than simply identifying which equation applies. Furthermore, articulation and reflection play a central role in developing integrated understanding. By requiring learners to explain why certain assumptions are appropriate, how changes in geometry or material properties influence stiffness and stability, and why numerical results are physically plausible, cognitive apprenticeship promotes metacognitive awareness and conceptual coherence. Exploration further supports transfer by encouraging students to apply learned reasoning strategies to novel configurations, a critical capability for professional practice.

Despite its strong theoretical alignment with the demands of mechanics education, cognitive apprenticeship is difficult to implement consistently in large enrollment undergraduate courses. Sustained, individualized dialogue, which is central to coaching, articulation, and reflection, is constrained by instructional time, class size, and staffing limitations. As a result, much of expert reasoning remains implicit, and students receive limited feedback on the quality of their conceptual understanding. These constraints motivate the exploration of GAI as a scalable mechanism for supporting cognitive apprenticeship in mechanics. When embedded within a principled pedagogical framework, GAI can facilitate interactive dialogue, adaptive questioning, and guided reflection that approximate aspects of expert coaching. Crucially, its value lies not in automating analysis or delivering answers, but in supporting the reasoning processes required to integrate strength, stiffness, and stability into a coherent understanding of mechanical behavior. This perspective positions GAI not as a replacement for instruction, but as an enabling tool for extending cognitive apprenticeship practices in contexts where traditional implementations are difficult to sustain.

3 Instructional Context and Module Design

The study was conducted in a junior level mechanical design course that integrates concepts from solid mechanics, structural analysis, and introductory design verification. By this stage in the curriculum, students have been exposed to individual topics such as axial stress, bending, buckling, and deflection in prior courses. However, they often lack experience applying these concepts concurrently within a single, realistic design context. The instructional goal of the course is therefore not only analytical correctness, but the development of integrated reasoning skills that mirror professional mechanical engineering practice.

To support this goal, a multi week instructional module on bolted connections was intentionally redesigned to foreground cognitive apprenticeship principles. Rather than treating bolted joints as a sequence of isolated checks, the module emphasized holistic verification of a structural connection under combined loading, requiring students to reason across strength, stiffness, and stability considerations. This redesign provided a natural setting for examining how AI supported dialogue could scaffold expert like reasoning in mechanics. The central instructional artifact was a five hole gusset plate connection joining a vertical and a horizontal structural member. The configuration was selected because it exhibits multiple interacting mechanical behaviors while remaining analytically tractable. Students were required to model the joint as a flexible system rather than a rigid node, explicitly recognizing that load transfer occurs through discrete bolts and that deformation and instability can influence performance even when strength criteria are satisfied.

The analysis tasks were structured around the three pillars of mechanical design. For strength, students evaluated local bearing stresses at bolt holes and compared these with nominal net section stresses to identify the governing failure mechanism. For stability, students assessed the potential for out of plane buckling of the gusset plate, accounting for geometric taper and partial rotational restraint provided by the bolt groups. For stiffness, students estimated load direction compliance by idealizing the plate as a tapered axial member and interpreting the resulting deflection in relation to system level behavior. Throughout the module, students were encouraged to consider how changes in geometry, material properties, or bolt layout would simultaneously influence all three performance dimensions.

GAI was introduced as a conversational scaffold embedded within this design workflow. Rather than functioning as a solution generator, the AI served as an adaptive prompting mechanism that guided students through expert like reasoning sequences. Typical prompts encouraged students to articulate load paths, justify simplifying assumptions, predict which failure mode would govern before calculation, and reflect on the physical plausibility of analytical or finite element results. The AI also prompted students to explore counterfactual scenarios, such as how increasing plate thickness would affect buckling resistance relative to bearing stress, thereby reinforcing the interconnected nature of mechanics concepts. By situating AI mediated dialogue within an authentic, multi constraint design problem, the module aimed to support cognitive apprenticeship practices that are difficult to sustain through traditional instruction alone. The gusset plate connection served not merely as an example problem, but as a shared cognitive workspace in which students could iteratively develop, test, and refine integrated mental models of mechanical behavior.

3.1 AI interaction protocol

GAI was integrated using a structured interaction protocol intended to support coaching and articulation rather than answer production. Students were instructed to use the AI in four phases.

Phase 1 (problem framing) required students to describe the load path, boundary conditions, and candidate governing mechanisms using their own words before requesting any feedback. Phase 2 (mechanism prediction) required a pre-calculation prediction of which failure mode would govern, and a brief justification based on geometry, loading, and expected deformation. Phase 3 (modeling decisions) required students to state explicit idealizations (e.g., bearing idealization, strip-buckling idealization, tapered-member stiffness idealization) and to explain why these were reasonable for the configuration at hand. Phase 4 (verification and reflection) required students to reconcile analytical results with physical interpretation and finite element visualizations, including at least one self-identified limitation or uncertainty in their modeling.

To mitigate hallucination risk and superficial correctness, the AI role was explicitly constrained: students were instructed not to request final numerical answers, and the AI was configured (or prompted) to respond with questions, checks, and reasoning prompts rather than authoritative claims. Students were further required to validate all reasoning using governing equations, free-body diagrams, and instructor-approved references, and to treat the AI as a coach whose output must be verified rather than as a source of truth.

4 Example Application: Gusset Plate Bolted Connection

The gusset plate bolted connection served as the central application through which cognitive apprenticeship principles were enacted and examined. This case was intentionally selected because it requires simultaneous consideration of strength, stiffness, and stability, mirroring the integrative reasoning demanded in professional mechanical design. Unlike canonical textbook problems that isolate individual failure modes, the gusset plate connection presents multiple competing mechanisms, none of which can be dismissed a priori without careful analysis. The geometry and bolt layout of the connection are shown in Figure 1a.

4.1 Concrete examples of AI-mediated coaching

To illustrate how the approach was enacted, we include brief excerpts from in-class student–AI dialogue. Student identifiers are anonymized; bracketed notes indicate the cognitive apprenticeship function represented.

> Student: I think tension will govern because the plate is thin.
> AI: Before choosing, can you explain how the load enters the plate through the bolts? Which region will see the highest contact pressure, and what stress state would that create? [coaching]
> Student: The bolt pushes on the hole edge, so bearing stress is local and high near

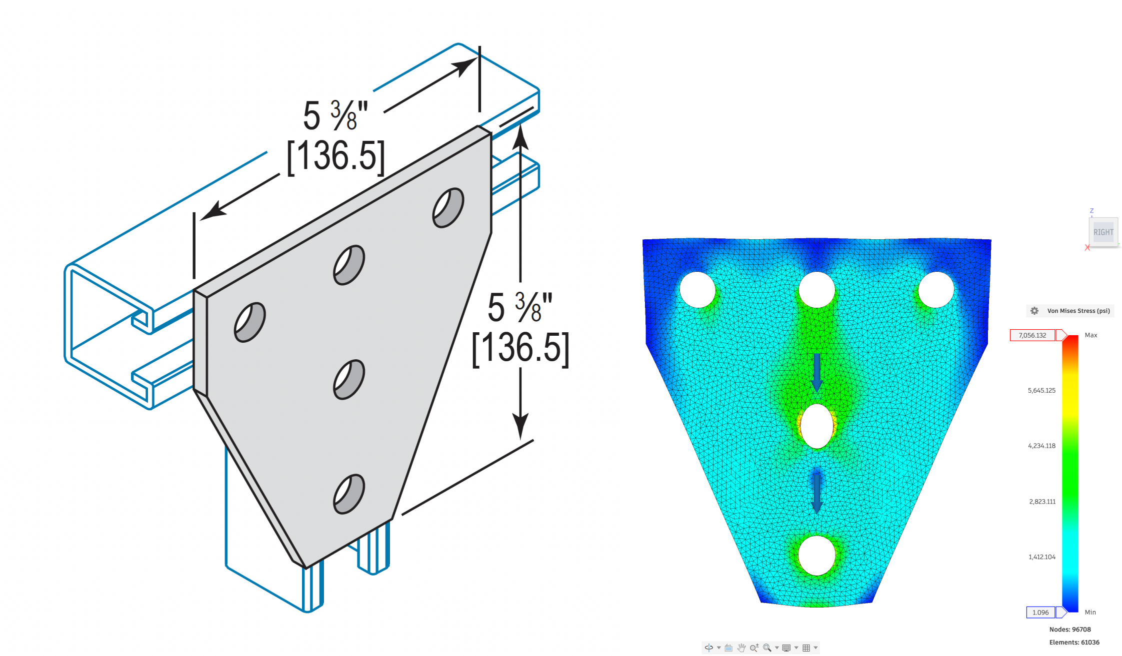

Figure 1: (a) Five-hole gusset plate connection geometry and bolt layout used in the instructional module. The configuration supports simultaneous evaluation of strength, stiffness, and stability. (b) Von Mises stress distribution in the gusset plate under compressive loading. Peak stresses localize at the lower bolt holes, indicating bearing-dominated strength behavior.

holes.
AI: Good. Now predict: if you increase plate thickness, which changes more: bearing stress, buckling resistance, or axial stiffness? Justify qualitatively first. [articulation]

Student: For buckling, I will treat the plate as a column.
AI: What is the effective strip width and boundary restraint between bolt lines? Can you justify your end conditions and the governing buckling mode you expect? [modeling + coaching]
Student: The bolts restrain rotation partially, so it is not pinned–pinned.
AI: Then write the assumptions explicitly and tell me what observation in the FE mode shape would confirm or contradict them. [reflection]

Students were first required to reason about strength in the context of load transfer through discrete fasteners. Rather than assuming uniform stress distributions, the analysis emphasized bearing-dominated stresses at bolt holes, where load is introduced into the plate. This framing challenged common student misconceptions that nominal net-section stress governs strength in all bolted members. As illustrated by the von Mises stress contours in Figure 1b, peak stresses localize at the lower bolt holes, confirming that local bearing behavior, rather than average membrane stress, controls yielding in this configuration.

Stability considerations introduced a qualitatively different mode of failure that could not be inferred from stress calculations alone. Students evaluated the potential for out-of-plane buckling of the

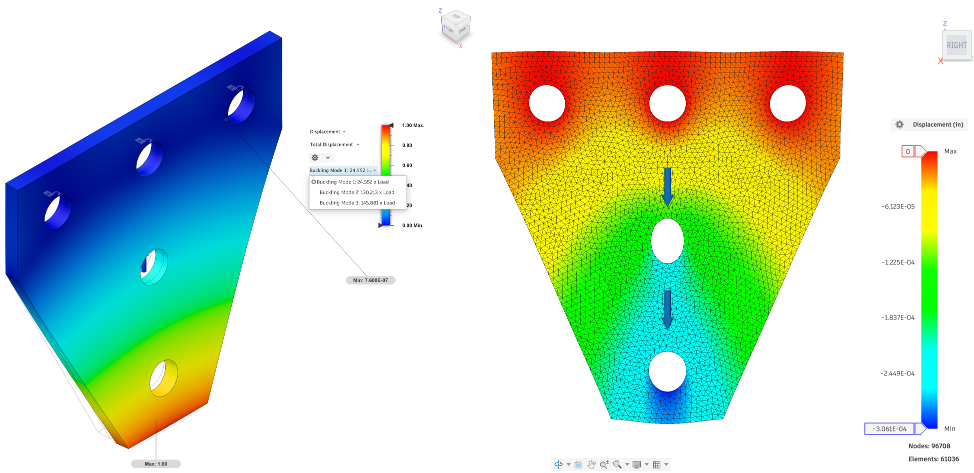

Figure 2: (a) First out-of-plane buckling mode of the gusset plate. The deformation pattern indicates a global strip buckling mechanism governed by geometry and bolt restraint. (b) Load-direction displacement field of the gusset plate. Deformation is dominated by axial membrane action, resulting in high stiffness despite thin geometry.

gusset plate by idealizing the tapered ligaments as equivalent strip elements with partial rotational restraint provided by the bolt groups. The first buckling mode, shown in Figure 2a, reveals a global strip instability extending between bolt rows rather than a purely local ligament buckle. This behavior underscores the dominant role of geometry, thickness, and restraint in stability analysis and highlights why strength-based checks alone are insufficient for safe design.

Stiffness analysis completed the triad by shifting attention from failure prevention to serviceability and system response. Students modeled the gusset plate as a tapered axial member to estimate load-direction compliance under vertical loading. The resulting displacement field, shown in Figure 2b, demonstrates that deformation is governed by axial membrane action over a short load-transfer length. This comparison helped students distinguish between local component compliance and overall joint deformation, reinforcing an important but often overlooked design insight.

Throughout the case study, GAI was used to scaffold expert-like reasoning rather than to automate analysis. AI-mediated dialogue prompted students to predict governing failure modes before performing calculations, justify modeling assumptions, and articulate why particular mechanisms controlled behavior. By repeatedly linking analytical results to the physical responses, the module fostered holistic reasoning across strength, stiffness, and stability.

The gusset plate case study provides a concrete context for articulating the cognitive apprenticeship basis underlying the instructional design and analysis in this study. Rather than treating cognitive apprenticeship as an abstract pedagogical framework, this section explicates how its core components were operationalized to support mechanistic learning of strength, stiffness, and stability in the context of mechanical design, and how student reasoning evolved as a result.

At the foundation of the cognitive apprenticeship approach is modeling of expert reasoning. In the mechanics context, modeling does not merely involve demonstrating solution steps, but making explicit how experts conceptualize load paths, anticipate governing failure modes, and select appropriate analytical idealizations. In the gusset plate module, expert reasoning was modeled by foregrounding questions such as where load is introduced into the structure, which regions are most likely to experience localized stress, and which geometric features control stability and stiffness. These questions framed the analysis before any calculations were performed, signaling to students that mechanics analysis is fundamentally about mechanism identification rather than equation selection.

Coaching and scaffolding were enacted through structured AI mediated dialogue that guided students toward productive reasoning pathways while preserving cognitive responsibility. Rather than directing students to specific formulas, prompts encouraged them to justify assumptions, compare competing failure mechanisms, and reason qualitatively about how changes in geometry or material properties would influence system behavior. For example, students were prompted to predict whether increasing plate thickness would primarily affect bearing stress, buckling resistance, or load direction stiffness, and to explain their reasoning before computation. This form of scaffolding aligns closely with expert practice, in which qualitative judgments precede detailed analysis.

Articulation and reflection were central to promoting integration across strength, stiffness, and stability. Students were repeatedly required to explain why certain mechanisms governed behavior and why others did not, both in AI mediated dialogue and in written reflections. These articulation tasks revealed shifts in student reasoning from checklist style verification toward more coherent mechanism based explanations. Reflection prompts further encouraged students to reconcile analytical results with physical intuition and finite element visualizations, supporting deeper conceptual understanding.

Exploration was supported by encouraging counterfactual reasoning and parameter variation. Students were asked to consider how alternative bolt layouts, plate thicknesses, or material choices would alter the balance among strength, stiffness, and stability constraints. This exploratory dimension helped students recognize that mechanical design is inherently a tradeoff driven process and that no single performance metric can be optimized in isolation. Importantly, this exploration extended beyond numerical sensitivity analysis to include qualitative reasoning about governing mechanisms.

Evidence for the effectiveness of this cognitive apprenticeship basis was drawn from multiple data sources, including transcripts of in class student AI interactions, structured student reflections, and written exam responses. Qualitative analysis focused on indicators of metacognitive awareness, explicit articulation of load paths, and integration of mechanics concepts across analytical domains. Compared to prior course offerings without AI supported scaffolding, students demonstrated greater clarity in identifying governing failure modes, more consistent use of physically grounded explanations, and fewer conceptual errors related to load transfer and boundary conditions.

Assessment rubric for conceptual reasoning Exam and reflection artifacts were evaluated using a reasoning-focused rubric intended to capture conceptual coherence rather than procedural correctness alone. The rubric emphasized: (1) mechanism identification (explicitly naming candidate failure modes and selecting a governing mechanism with justification), (2) modeling justification (stating assumptions and linking them to geometry, loading, and boundary conditions), (3) physical interpretation (explaining what computed quantities mean and checking plausibility), and (4) integration across strength, stiffness, and stability (articulating tradeoffs and cross-effects of design changes). Scores were assigned using consistent criteria across offerings; representative rubric descriptors are provided in Table 1.

Table 1: Reasoning-focused rubric dimensions used for exam and reflection artifacts.

Dimension	Descriptor (evidence in student work)
Mechanism identification	Names plausible mechanisms; selects governing mechanism with justification.
Modeling justification	States assumptions; links idealizations to geometry, loading, and restraint.
Physical interpretation	Interprets results; checks plausibility; identifies limitations or uncertainties.
Concept integration	Connects strength, stiffness, stability; explains cross-effects of parameter changes.

Quantitative comparisons of exam responses further support these observations. While overall numerical performance showed modest improvement, more substantial gains were observed in the coherence and completeness of written explanations. Students were more likely to justify modeling assumptions, connect equations to physical behavior, and recognize when certain checks were non-governing. These outcomes suggest that the cognitive apprenticeship approach primarily enhanced conceptual understanding and reasoning quality rather than rote procedural performance. To provide short-term quantitative context, we compared reasoning-focused rubric outcomes on matched exam prompts with a prior course offering that did not include AI-mediated scaffolding. Table 2 reports descriptive comparisons; inferential claims are intentionally avoided due to cohort and implementation differences.

Table 2: Descriptive comparison of reasoning focused outcomes on matched exam prompts (measured on a 1 to 5 scale).

Outcome metric	Prior offering	AI-scaffolded offering
Mechanism identification score (mean)	4.0	4.3
Modeling justification score (mean)	3.6	4.1
Physical interpretation score (mean)	4.1	4.4
Concept integration score (mean)	3.2	4.3
Common conceptual error rate (%)	30%	11%

Taken together, these findings indicate that GAI can effectively support a cognitive apprenticeship basis for mechanics education when embedded within a carefully structured instructional design. The AI functioned not as a source of answers, but as a mechanism for sustained dialogue, guided articulation, and reflective reasoning. By making expert thinking visible and engaging students in mechanistic reasoning across strength, stiffness, and stability, the approach supports the development of integrated mental models essential for professional mechanics practice.

5 Limitations and Future Work

Several limitations of this study should be acknowledged. First, the findings are based on short term learning outcomes observed within a single offering of a junior level mechanical design course. While improvements in conceptual coherence, articulation of reasoning, and identification of governing mechanisms were observed, the extent to which these gains persist over time or transfer to subsequent courses remains an open question. Longitudinal studies following students into advanced mechanics or capstone design courses would provide valuable insight into the durability and transferability of the observed learning effects.

Second, the instructional intervention was implemented within a specific institutional and curricular context. The generalizability of the results to other course structures, class sizes, or student populations warrants further investigation. Future work could examine how AI supported cognitive apprenticeship scales across different mechanics topics, such as fatigue, fracture, or dynamic stability, and how it interacts with varying levels of prior student preparation.

Third, while GAI was intentionally constrained to function as a reasoning scaffold rather than a solution generator, the design of effective prompts remains a nontrivial pedagogical challenge. Refinement of prompt structures, sequencing, and levels of specificity is needed to better align AI mediated dialogue with evolving student expertise. In particular, future studies should investigate strategies for fading scaffolds as students develop greater independence, ensuring that reliance on AI support diminishes rather than persists.

Finally, this study focused primarily on conceptual and reasoning outcomes rather than affective or motivational factors. Future research may explore how AI supported cognitive apprenticeship influences student confidence, epistemic beliefs about mechanics, and perceptions of professional preparedness. Such work would further clarify the role of GAI in supporting not only learning outcomes, but also identity development within engineering education.

The interaction protocol is designed to scale to larger enrollments by shifting routine coaching and articulation prompts to structured AI dialogue, while preserving instructor responsibility for content validity and assessment. Scaling requires a shared prompt starter and guardrails, assignment structures that require students to externalize assumptions and verification steps, and rubric aligned evaluation of reasoning quality. Future offerings will test scaffold fading strategies in which AI prompting is gradually reduced as students demonstrate independence, thereby encouraging transfer of expert like reasoning without persistent reliance on AI support.

This work suggests several design principles for embedding GAI in mechanics without diluting rigor. First, constrain the AI to coaching behaviors that elicit student reasoning rather than producing final answers. Second, anchor interaction around mechanisms such as load paths, governing failure modes, and physically meaningful interpretation before equations. Third, require explicit assumption statements and verification steps that tie AI dialogue to governing equations and trusted references. Fourth, support reflection by prompting plausibility checks and reconciliation with computational or experimental evidence, and plan for scaffold fading to promote independence.

6 Conclusions

This paper demonstrates that GAI can operationalize cognitive apprenticeship principles in undergraduate mechanics education when embedded within a carefully designed instructional framework. By situating AI mediated dialogue within an authentic bolted connection design task, this work extends prior research into the domain of undergraduate mechanics, where interdependent reasoning about strength, stiffness, and stability is central to professional competence. The findings indicate that by supporting modeling, coaching, articulation, and reflection, AI mediated dialogue helped students shift from checklist based analysis toward integrated mental models of mechanical behavior. Specifically, this study contributes an implementable instructional design and a worked gusset plate case study that externalizes expert reasoning about load paths and failure mechanisms.

Quantitative and qualitative evidence suggests that this approach primarily enhances reasoning quality, as evidenced by substantial gains in mechanism identification and modeling justification scores compared to prior offerings. These results confirm that GAI can function as a scalable mechanism for extending guided dialogue and reflective practice beyond the constraints of traditional classroom interactions. Ultimately, GAI holds promise as a pedagogical collaborator in mechanics education when its role is carefully constrained and aligned with disciplinary goals. By grounding AI use in cognitive apprenticeship theory and anchoring it to physically meaningful engineering problems, this work contributes evidence based insight into how emerging technologies can be leveraged to enhance the intellectual rigor of undergraduate engineering education.

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