A Methodological Framework for Modernizing Engineering Course Content with Large Language Models

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A Methodological Framework for Modernizing Engineering Course Content with Large Language Models

Abstract

Rapid changes in educational technology and student expectations present challenges for engineering educators. Although core engineering methods often remain the same over time, course materials become outdated in presentation and pedagogical approach. This paper presents a methodological framework for using Large-Language Models (LLMs) to modernize engineering course content with a case study in an advanced technical analysis course. The methodology follows a phased approach that is designed to be repeatable and to verify the accuracy and completeness of the course content. During the first phase, an LLM is used to map outdated text-heavy content to a modern format using a LaTeX template. The second phase involves introducing the LLM to the Entrepreneurial Mindset (EM) developed by the Kern Entrepreneurial Engineering Network (KEEN), emphasizing curiosity, making connections, and creating value, and asking it to relate the modernized content to various engineering disciplines. The final phase involves human-in-the-loop review by the instructor to ensure that (1) all content has been successfully mapped, (2) the content is accurate, and (3) the connections are correct and relevant. This study demonstrates a repeatable process for content transformation that can be applied to modernize the wealth of legacy engineering content that exists in order to promote engagement with students. The process is presented as a systematic workflow with sample prompts to serve as a blueprint for other educators. In addition, a case study for an advanced technical analysis course demonstrates that the framework successfully translates complex technical content and code.

Keywords

Large-Language Models (LLMs), Course Modernization, Entrepreneurial Mindset (EM), AI in Education, Technology-Enhanced Learning, Content Transformation

Introduction

Although technology advances rapidly, instruction in engineering fundamentals, particularly mathematically rigorous content, tends to evolve slowly. In contrast, instructional practices and student expectations have undergone accelerated change in recent years. The result is content that is solidly based in technical rigor but pedagogically stale. As computational tools, instructional techniques, and student expectations evolve over time, content modernization requires careful preservation of technical rigor while updating explanations, examples, and code-based demonstrations. The tight coupling of visual representations of the engineering problem, derivation of mathematical equations, and computational workflows to arrive at a solution presents unique challenges for engineering educators. The time consuming process of content modernization is therefore more difficult to scale when revising a course manually. Until now, many applications of artificial intelligence in education have focused on personalized tutoring, automated assessment, or performance prediction [1, 2]. There are far fewer works that have addressed the systematic modernization of existing curricula. LLMs translate text into embeddings capable of capturing semantic meanings and then manipulate the latent space to accomplish tasks such as text generation, reasoning, and knowledge inference. Especially when restricting context to a set of existing content, using instructions with instructor-provided constraints, and providing iterative human-in-the-loop feedback, LLM becomes an enabler of content transformation, but not a replacement for instructor expertise.

The main contributions of this engineering educational approach are as follows:

1. A framework and workflow for using Artificial Intelligence (AI) to modernize engineering content.
2. Development of a constraint-based mapping prompt for modernizing content and an EM integration prompt.
3. An application of the framework and prompts in a technically dense, computationally rigorous engineering technology course.

By focusing on a methodology that is reproducible and transferable rather than simply automated, this work aims to be applicable across a wide range of engineering and engineering technology topics.

Background and Related Work

Existing work in applications of AI in education shows a strong preference for applications in personalized tutoring, automated assessment, and predictive analytics [1, 2]. In addition, most studies do not support the interaction between the instructor and tool [3]. Some studies focused on understanding how students use AI and examining the ethical implications of these activities [4, 5].

AI for Tutoring

AI systems can adapt instruction to individual learners by identifying prior knowledge and gaps, adjusting difficulty levels in real time, and recommending targeted practice problems or resources [1]. By analyzing student behavior, the learning experience is personalized to focus on areas of weakness, skip content they have already mastered, and learn at their own pace [6]. A recent study showed higher learning gains for university physics students who engaged with an AI tutor than those who participated in an active lesson in class [7]. AI tutoring systems offer on demand availability, enabling learners to access instructional support whenever needed, and can scale efficiently to serve large student populations, especially non-traditional or online students who may have limited access to in person support [8]. These systems can increase the variety of ways that learners can interface with content by leveraging LLMs to generate alternative explanations, examples and multimodal representations, such as text and visual representations [9, 5].

AI for Assessment

AI has been used to assess student work to provide real-time feedback, understand complex performance data, and provide timely scoring and feedback [3, 6]. Applications have been developed and found to reduce the burden of grading text-heavy student responses [10]. However, Tobler [10] do note challenges with evaluating non-text-based content, including mathematical equations and images, which are usually a large part of engineering solutions. By uncovering patterns in student work, AI identifies misconceptions and enables early intervention [6]. AI-supported assessment data has been proposed to monitor mastery of student learning outcomes and to inform continuous curricular improvement by providing insights to educators [3]. Some textbook publishers and educational technology providers have begun experimenting with these capabilities by embedding AI-driven homework systems, adaptive quizzes, and analytics dashboards into digital course platforms, particularly in large-enrollment STEM courses. These approaches could offer advantages such as scalability for large student populations, timely and individualized feedback, diagnostic insight into student learning, and reduced grading workload for instructors.

AI for Predictive Educational Analytics

AI learning analytics techniques have been successfully used in engineering education to analyze diverse data sources, with the goal of enhancing overall course attainment levels [11]. Early intervention in engineering is particularly valuable because learning is cumulative, so difficulties in foundational topics often propagate. Predictive analytics takes early intervention a step further by identifying students who are not yet struggling, but are likely to struggle in the future [11]. At the instructional level, predictive analytics has been used to inform course adjustments and continuous improvement by revealing patterns across cohorts and aligning evidence with learning outcomes [11].

AI for Content Transformation

Initial efforts in content transformation are promising, such as an experiment by Elidan and Haramaty [12], which transformed textbooks to multimodal content representations for individual learners. However, this educational intervention did not allow for instructor in the loop validation of content. Brown, Talbert, and Roberts [13] studied mapping between curriculum frameworks and noted that LLMs are better suited as assistants than replacements for human instructors. Rutecka et al. [14] mapped the curriculum and syllabi in economics and found that while LLMs can produce plausible course structures, they are not yet capable of creating complete and compliant curricula and must be used subject to human-in-the-loop oversight.

Table 1 shows a breakdown of typical tasks that AI tools generally complete in existing workflows. There is a noticable gap in AI for content transformation, as there is not only limited work in this area, but much of it is limited to format transformation without instructor feedback.

There are also limited opportunities to add connections that enable enhanced career-centered development skills such as EM.

Risks and Design Considerations for AI in Engineering Education

As LLMs still face major challenges with hallucination, bias, and lack of transparency, it is critical to take care when implementing these systems [15, 16]. These flaws imply the potential to amplify inaccuracies and propagate inequities when used over large amounts of educational content. A common theme in reviews of tutoring, assessment, predictive analytics, and emerging content transformation applications is the need for well-defined constraints and human oversight [3, 1, 2]. In engineering education, this includes ensuring that AI tools are scoped to well-defined content, provided clearly formulated constraints, and require instructor review and judgement.

Table 1: Examples of typical tasks in existing work broken down by AI role to determine if AI is used to transform curricular artifacts.

Role	**Typical Tasks**	**AI used for content transformation?**
Tutoring	Adaptive feedback, step-by-step guidance, chatbots as tutors	Rarely; focuses on interaction, not content mapping
Grader/Assessor	Automated scoring, rubric-based feedback	No; operates on student work not course materials
Predictive Analytics	Performance prediction, risk identification	No; informs instructors not course materials
Content Transformation← ***Proposed Contribution***	Systematic updating and reformatting of existing content; multimodal transformations	Partial; many focused on format conversions or course objective mapping

Framework for LLM-Assisted Course Content Modernization

The LLM-assisted framework proceeds sequentially from content mapping and modernization to the integration of engineering mindset connections. There are also iterative revisions where the instructor actively makes or requests modifications to how the content is mapped. The process is only considered complete when the instructor is satisfied that the content is correct and sufficiently updated. The process can be repeated for each chapter or module in a given course until all content has been mapped.

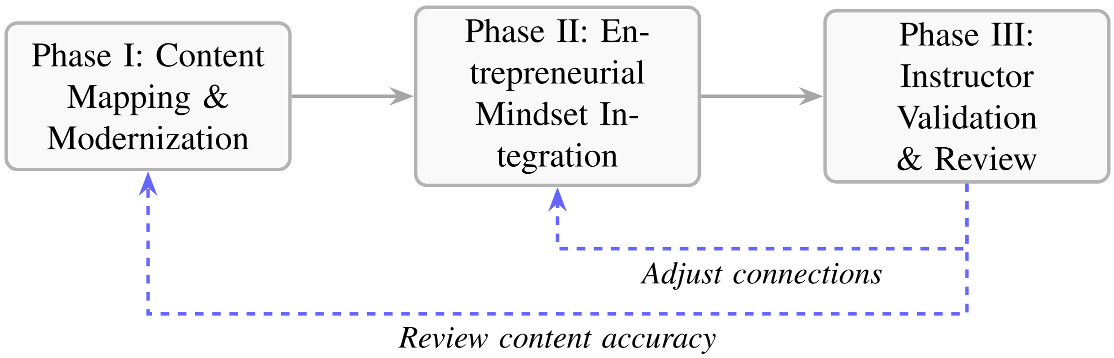


Figure 1: Content transformation framework with instructor feedback loops. Dashed arrows indicate iterative revision cycles where the instructor makes or requests modifications to content mapping (Phase I) or EM connections (Phase II) based on validation outcomes.

Phase I: Content Mapping and Modernization

The purpose of Phase I is to map the content without modifying the underlying technical scope. The initial input to the workflow is a set of scope-limited content along with a prompt that emphasized instructor provided constraints. The constraint-based mapping prompt was designed to ensure success in Phase I is shown below:

Constraint-based Mapping Prompt: Map the provided instructional content into the modern LaTeX-based lecture format. Preserve all mathematical definitions, equations, and examples while reframing text-heavy explanations into worked examples, visualizations, and computational demonstrations where appropriate. The transformed content should remain aligned with the original scope and be suitable for engineering technology students using MATLAB.

The first sentence provides the input content and output format, which limit the scope and enforce structural consistency, respectively. The remaining sentences provide the constraints that define the transformation behavior. By separating the overall task into components with distinct roles, the designed prompt ensures that the goals of Phase I are met.

In particular, limiting the input scope limits the likelihood of hallucinated prerequisite topics and eases the human review process by limiting the content magnitude. Specifying the output format ensures visual and structural consistency throughout the final content. In fact, templates can be provided for each type of content the LLM is asked to generate. For example, a template slide with a mathematical or code-based example.

Finally, the constraints provide rules for the LLM to follow while mapping the content. Critically, each constraint serves a different function as shown in Table 2.

The prompt constraint-based mapping prompt specifically does not allow cross-disciplinary examples or extensions that enable value creation and the inspiration of creativity.

Table 2: Mapping of Phase I prompt constraint to instructional functions.

Prompt Constraint	**Instructional Function**
Preserve all mathematical definitions and examples.	Ensure content fidelity
Reframe text-heavy explanations into worked examples, visualizations, and computational demonstrations where appropriate.	Modernize pedagogy
Remain aligned with the original scope	Enforces curricular boundary
Suitable for engineering technology students	Calibrates course focus for audience

Phase II: Integrating the Entrepreneurial Mindset

Moving from Phase I to Phase II, the framework allows for the relaxation of structural constraints and explicitly asks the LLM to introduce application-oriented examples while maintaining contextual and scope constraints. In order to enable this work, a general EM Integration Prompt was designed.

EM Integration Prompt: Extend the modernized technical content by embedding application-oriented examples that encourage curiosity, make connections across engineering disciplines, and illustrate value creation. Applications should remain aligned with the original technical scope, avoid introducing new prerequisite theory, and be suitable for engineering technology students. Examples should be interpretable analytically and implementable computationally (e.g., in MATLAB), with an emphasis on interpretation rather than derivation.

Table 3 shows how each part of the prompt serves to enable a unique function critical for the success of Phase II. Rather than explicitly defining the 3C's from the KEEN EM, i.e., curiosity, connections, and creating value, they were implicitly implemented in the prompt. In addition, the technical scope is firmly limited to that in the output from Phase I to reduce the risk of scope creep. Finally, the types of examples are specified to be both analytical and computational to ensure that both of these broader problem types are present, matching the overall course objectives.

Phase III: Human-in-the-Loop Validation and Review

Unlike Phases I and II, Phase III shifts control to the instructor to ensure academic responsibility, pedagogical accountability, and ethical AI use. The instructor follows the following steps to validate the content modernization and mapping:

The evaluation process focused on three primary criteria: technical accuracy, pedagogical alignment, and scope and relevance. Technical accuracy included verification of correct notation and equations, proper computational syntax and behavior, and the validity of both analytical and numerical results. Pedagogical alignment emphasized ensuring that course objectives were met, that the content was appropriate for the course timeline, and that concepts were presented in a logical sequence, with definitions and foundational material introduced prior to applications.

Table 3: Mapping of Phase II prompt components to instructional functions.

Prompt Component	Text from Prompt	Function
Contextualization	Embed application-oriented examples	Shifts content from abstract mathematics to contextualized engineering
EM Integration	Encourage curiosity, connections, and value creation	Operationalizes EM outcomes
Scope Control	Remain aligned with original technical scope	Prevents topic drift and theory inflation
Audience Control	Avoid assuming prior engineering theory knowledge	Calibrates course focus for audience
Analytical and Computational Exploration	Examples interpretable analytically and implementable computationally	Reinforces dual math–computation workflow
Rigor Preservation	Emphasis on interpretation rather than derivation	Preserves rigor while prioritizing understanding

Scope and relevance considerations involved identifying and removing content drift, checking for the inclusion of unintroduced or unsupported theory, and ensuring alignment with the intended student learning outcomes.

Once errors or inconsistencies are found, they can be handled in two ways, depending on the instructor's preference. The first way is direct correction. This is most appropriate for small corrections that are easily fixed or sticky errors, such as LLM, which has a difficult time correcting. Another option is targeted regeneration. Since the output format is text-based, the instructor can simply paste a slide or slides to be revised along with a request for update.

Figure 2 shows the full three-phase workflow with feedback throughout. In general, it is better to ask the LLM to edit content during Phases I and II when it has just mapped the slides. It is more difficult for the LLM to avoid scope creep when it is further removed from the mapping process. Then in Phase III, the instructor can fine-tune the material through detailed validation.

Case Study: Advanced Technical Analysis Course

Course Context and Materials

The bachelor's degree in the Engineering Technology (ET) programs at Old Dominion University requires mathematics up to Calculus I (differentiation and integration of algebraic and transcendental functions of one variable) and algebra-based Physics I and II, whereas regular engineering degrees would additionally require Calculus II (techniques of integration, polar coordinates, infinite series, solid geometry, vectors, lines, and planes), Calculus III (partial derivatives, multiple integrals, and vector calculus), and Differential Equations courses, as well as calculus-based physics. While the additional math concepts are still needed for the presentation of

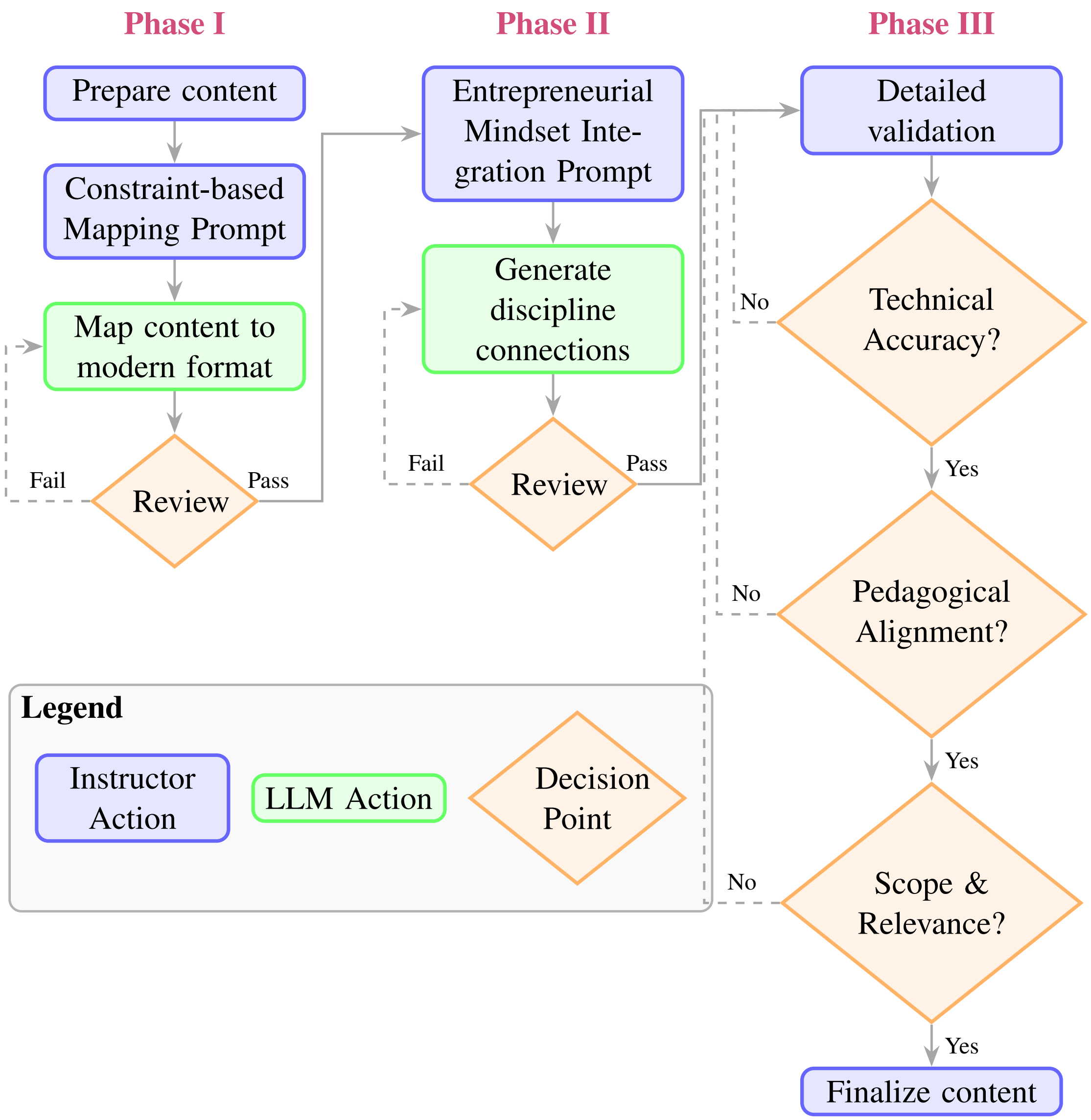


Figure 2: Detailed workflow showing instructor and LLM actions at each phase. Blue, green, and orange are used to represent instructor actions, LLM tasks, and decision points, respectively. Dashed arrows in Phases I and II indicate feedback loops where the LLM is asked to regenerate content. In Phase III, the instructor directly fixes any issues identified during validation.

the engineering results, in the engineering technology courses, there is less focus on the analytical and derivation aspects, and the higher-level math is needed mostly for students to be able to understand and follow the course presentation, and not to perform rigorous math derivations. To introduce engineering technology students to the higher-level mathematical concepts required in their coursework, the ET curriculum includes a 300-level course entitled Advanced Technical Analysis [17, 18]. This course covers a broad range of foundational topics, including matrix analysis and the solution of simultaneous equations using matrices; a review of single-variable differential and integral calculus; the solution of differential equations using classical time-domain methods; the application of Laplace transforms to differential equations; an

Table 4: Summarization of key features for content mapping framework.

	Phase I	**Phase II**	**Phase III**
Goal	Map content into modern instructional format	Contextualize content	Ensure accuracy, relevance, and completeness
Nature of LLM output	Structurally constrained transformation	Directed expansion and contextualization	Reviewed, corrected, and finalized
Risk being managed	Content loss	Misalignment or superficial applications	Technical errors or pedagogical mismatches
Typical Artifacts	Slides, worked examples, MATLAB code	Application examples, discussion prompts	Final lecture materials

introduction to probability and statistics; curve fitting and correlation techniques; and an introduction to three-dimensional vector analysis. A former ET faculty member specifically developed a textbook for this course, covering all the mathematical topics listed above with MATLAB and hands-on solutions [19]. Along with math concepts, students are also introduced to programming through MATLAB. Basic programming concepts are taught, including if/else tests and for/while loops, as well as MATLAB solving of all the math-type problems presented in the rest of the course. Plotting is covered in detail, as visual presentation of results is essential in all engineering. Simulink is also introduced, with applications mostly in system modeling and solving differential equations. For most students, this is the first course in which they learn programming. Electrical engineering technology students are also exposed to programming through microprocessor courses (C/C++ programming).

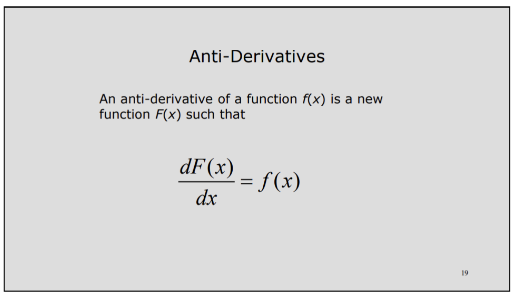
Application of the Framework

While a variety of state-of-the art LLM tools would be appropriate for the application of this framework, this paper will present results generated by ChatGPT using the GPT-5 or GPT-4o [20]. The original course consisted of 23 lecture slide decks that were fragmented across textbook chapters and content topics. Using the proposed framework, all content was modernized and reorganized into 14 slide decks. Even though the total number of slides was reduced from 464 to 305, representing a 34% reduction, there was no removal of technical content, but rather a shift from text-heavy explanations to worked examples, visualizations, and MATLAB scripts presented during instruction. This represents a clear, intentional shift toward the example-driven, computationally-focused instruction that the framework is designed to provide.

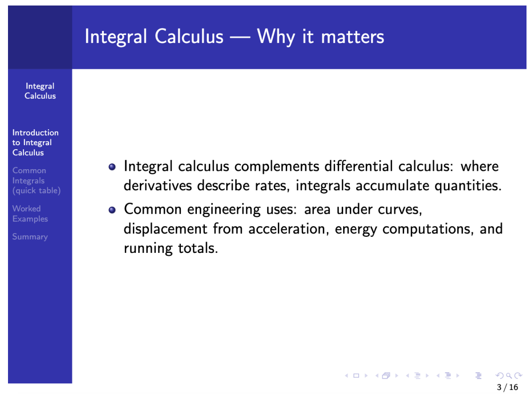
The prompts for Phase I and II needed to be made specific for this course. The prompt example in Figure 3 shows a single instantiation of the general constraint-based mapping prompt designed for Phase I. Figure 4 shows slide-based content before and after the Phase I mapping process. The dense explanatory text has been removed to improve content accessibility. There is a noticeable shift from definition centric to motivation centric presentation aimed at engaging the learners.

Map the $\underbrace{\text{content from ENGT305\_Fall2023\_Lecture14 starting at slide 12}}_{\textbf{Input}}$ into the $\underbrace{\text{LaTeX Beamer template}}_{\textbf{Output Format}}$ we have been using. $\underbrace{\text{Preserve all mathematical definitions and examples.}}_{\textbf{Constraint}}$ $\underbrace{\text{Replace text-heavy explanations with worked examples}}_{\textbf{Constraint}}$ and $\underbrace{\text{MATLAB code where appropriate.}}_{\textbf{Constraint}}$

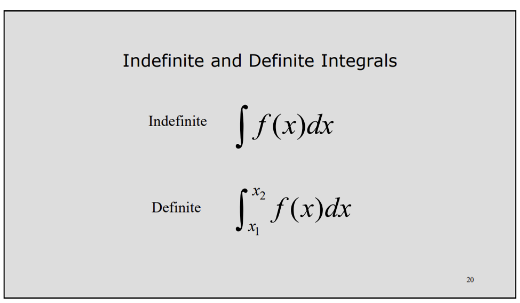
Figure 3: A constraint-based mapping prompt labeled to show how each part represents a critical component, i.e., input, output format, constraints, to ensure that the task for Phase I is complete.



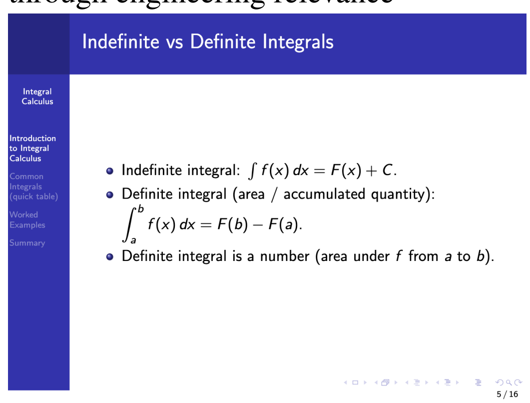
(a) Text-heavy integral calculus definition



(b) Modernized introduction with motivation through engineering relevance



(c) Abstract presentation of indefinite and definite integrals



(d) Modernized presentation emphasizing interpretation

Figure 4: Representative before-and-after examples illustrating the transformation of abstract, text-heavy instructional slides into context-driven, application-motivated material using the proposed LLM-assisted framework. Using Phase I of the proposed framework, mathematical scope is preserved while pedagogy is modernized.

However, the mathematical content, learning objectives, and formal rigor are preserved in the modernized version of the content. This provides a good foundation for the EM examples to be integrated in Phase II.

Figure 5 shows a specific example prompt that was used based on the general EM prompt. At this

For the modernized lecture content, $\underbrace{\text{add applied engineering examples}}_{\textbf{Contextualization}}$ that help students

see where the mathematics is used. Use models from $\underbrace{\text{vibrations, beams, or system response}}_{\textbf{Disciplinary Connections}}$

$\underbrace{\text{Provide all governing equations so prior engineering theory is not assumed.}}_{\textbf{Rigor Preservation}}$

$\underbrace{\text{Keep examples aligned with the existing lecture scope}}_{\textbf{Scope Control}}$ and $\underbrace{\text{suitable for engineering technology students.}}_{\textbf{Audience Control}}$

$\underbrace{\text{Include MATLAB plots or scripts enabling parameter exploration and interpretation.}}_{\textbf{Computational Exploration}}$

Figure 5: An example EM integration prompt labeled to show how each part represents a critical component that maps to a function to ensure that the task for Phase II is complete.

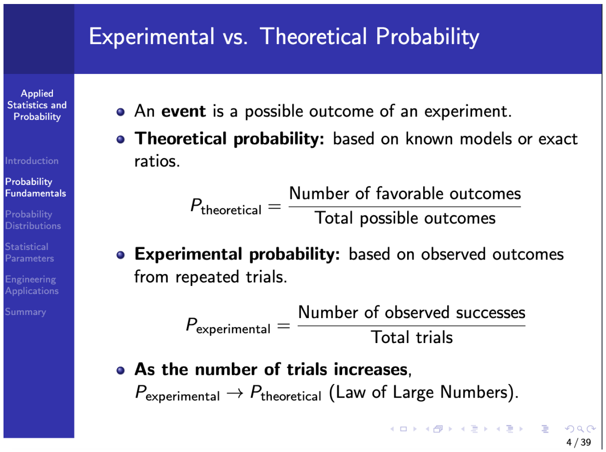
stage, many of the requirements were repeated back to the LLM in iterative prompts through conversation to request updates to fine tune the examples. This iterative process required careful review of the generated output and the formulation of specific requests for refinement, including the explicit use and presentation of relevant engineering equations, avoidance of assumptions regarding prior theoretical knowledge beyond the course prerequisites, incorporation of MATLAB implementation and graphical visualization of the solution, and consideration of whether the problem could be solved both analytically by hand and computationally using MATLAB.

Figure 6 shows example of a MATLAB exploration generated using Phase II. The definition slide (Figure 6a) is included for reference as the output of Phase I and the corresponding input of Phase II. Phase II reinforces the technical rigor without introducing any additional mathematical content. It stimulated curiosity by allowing students to investigate increasing the number of trials in an experiment in order to observe the effect on the experimental probability. This supports connections by enabling discussions around reliability of engineering processes. By examining the results of the experiment (Figure 6d) students start to ask questions about convergence, variance, and reliability which is an important step toward creating value by strengthening their ability to quantify results, while also communicating levels of certainty and confidence.

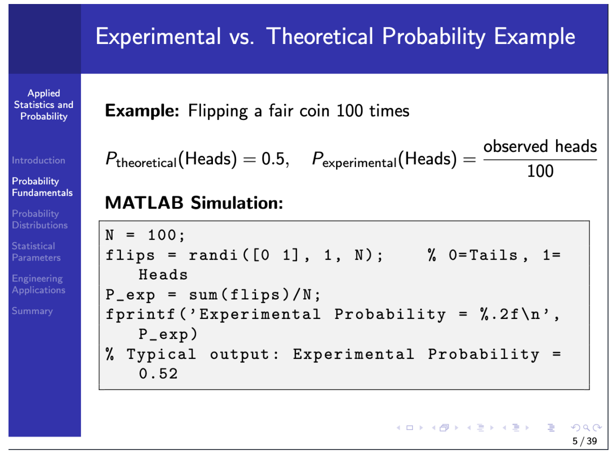
For Phase III, all content was reviewed prior to using it with students. All code was run in MATLAB to ensure that it was correct and executed successfully. Mathematical formulas were checked to ensure factual accuracy and readability. Finally, content was reviewed to ensure that no content was lost and no additional content was added during the process.

Discussion and Outcomes

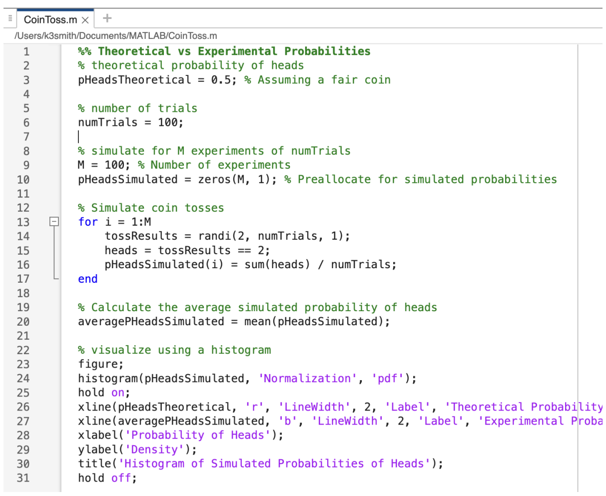
This study proposes a framework for modernizing engineering course contents, utilizing large language models (LLMs). According to the results, LLMs have a huge potential to be one of the strong AI tools for course content modernization, particularly in engineering. The proposed framework preserves technical content, i.e., mathematical definitions, equations, and examples, while enabling a pedagogical shift from text-heavy explanations to example-driven and visualization approaches. This is intended to provide a balance in engineering technology



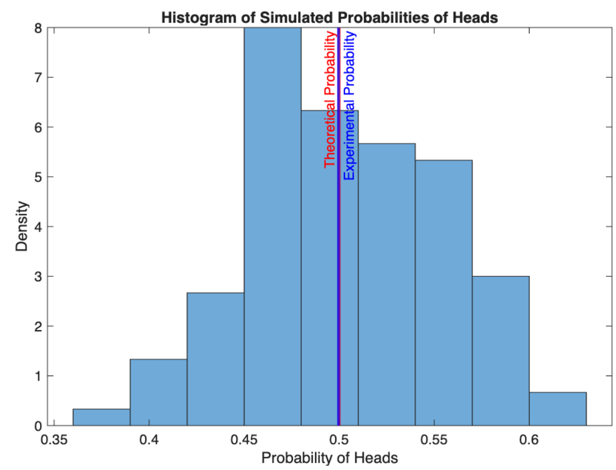
(a) Theoretical and experimental probability definitions.



(b) Experimental probability setup.



(c) MATLAB implementation used to enable parameter variation and iterative exploration.



(d) Simulation results illustrating convergence of experimental probability with increasing trials.

Figure 6: Phase II example integrating the entrepreneurial mindset into probability instruction. Abstract probability definitions are contextualized through computational experimentation, visualization, and interpretation without expanding mathematical scope.

education, i.e., updating course materials without removing core technical content, and still meet the course outcomes and student expectations. Additionally, the framework supports constraint-based prompting in Phase I, which is crucial for mitigating common risks associated with LLMs, such as hallucinations, inappropriate responses, and assumptions.

The integration of the EM in Phase II shows how LLMs can add more value and support curricular enhancement. The KEEN EM is treated as a pedagogical lens for engineering decision-making. The existing technical content is extended by embedding application-oriented examples along with the KEEN 3C's, i.e., curiosity, connections, and creating value. One interesting finding from this study, when reviewing the prompts used, was that the KEEN 3C's, curiosity, connections, and creating value, were never formally defined for the LLM. Instead, they were stated as encouraging curiosity, making connections, and creating value, and then operationalized with persistent feedback to direct the LLM to provide relevant examples as shown in Table 5. From a pedagogical perspective, this highlights the importance of prompt engineering as an instructional design activity.

Another interesting result is the significant reduction in total slide count without loss of technical content coverage, i.e., 34%, by shifting from explanations into worked examples and visualizations. This helps both the instructor and students; instead of spending more time with text-heavy explanations, they focus on understanding the mathematical formulations with computational interpretation.

The proposed framework also involves the human-in-the-loop validation process in Phase III. This allows the instructor to validate the content modernization and mapping through the technical accuracy, pedagogical alignment, as well as scope and relevance. The use of LLM makes the process more effective and reduces the initial effort required by the instructor to modernize legacy materials.

Although the proposed framework provides several advantages, particularly for content modernization, several limitations can be considered. First, the instructor is expected to have expertise in both the subject and in evaluating LLM-generated outputs. While LLMs are becoming more widely used this does make the framework difficult to access for all instructors. Second, the initial validation metrics with the process are defined, but additional metrics are needed to evaluate the LLM uncertainty and the hallucination rate to improve the trustworthiness of the LLM.

Conclusions and Future Work

This educational intervention presents a repeatable, instructor-centered framework focused on transforming content rather than replacing it. The framework allows instructors to keep up with changing instructional methods and student expectations without sacrificing technical rigor. The transformation process is demonstrated using a core engineering technology course that covers applications of upper-level mathematics in MATLAB. This course represents a challenging test case, as it requires a bridge between foundational mathematics, such as functions and graphing, up through differential equations, incorporated computational tools, and the integration of examples that make connections, encourage curiosity, and create value.

The future work includes integrating student-centered activities and assessments that incorporate the EM. There is evidence that mastery-based learning is effective in supporting EM activities.[21] indicating that mastery-based, student-centered learning activities may be a good target for this work. In addition, it would be prudent to study the preservation of the content in a quantified way. Specifically, investigating the trustworthiness of various LLMs in preserving the content after Phase I would be an interesting investigation.

Table 5: Operationalization of the KEEN 3C's Through Instructor Prompts and LLM Outputs

Instructor Prompt / Constraint	**LLM Output**	**KEEN 3C Supported**
Integrate examples engaging mechanical, electrical, civil, and manufacturing ET students	Discipline-specific application examples embedded alongside mathematical methods	Connections
Stick strictly to the content in the provided PDFs	Scope-limited examples aligned with legacy material and learning objectives	Creating Value
Add poll questions to slides	Prediction-based and concept-check questions prompting student exploration	Curiosity
Show how step size affects numerical differentiation accuracy	Comparative MATLAB scripts and plots visualizing error versus step size	Curiosity
Include application problems without assuming engineering theory	Model-based problems with equations provided, emphasizing interpretation	Creating Value
Improve organization for two 75-minute lectures	Progressive sequencing from concepts to applications and validation	Creating Value
Demonstrate domain and range using stress–strain data	Visualization-driven examples linking math behavior to physical constraints	Connections, Curiosity

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