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AI-Driven Flipped Classroom Strategies for Introductory Thermodynamics

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I have been teaching Thermodynamics to undergraduate students for over ten years while serving in various capacities, from Tutor to TA to lecturer. This paper reflects on some techniques that I am utilizing in my classroom to improve student learning. I am working as an Assistant Teaching Professor of Engineering at Penn State Beaver Campus.

AI-Driven Flipped Classroom Strategies for Introductory Thermodynamics

It has long been demonstrated that classroom engagement increases when students are involved in hands-on activities and problem-solving tasks—an insight that forms the backbone of the flipped classroom model [1], [2]. The flipped classroom, first popularized in the early 2000s as digital technologies made pre-class instructional videos more accessible, emerged as a response to longstanding evidence that students learn more effectively when they can engage with foundational material at their own pace [3], [4]. Self-paced learning affords students the time necessary to reflect, revisit difficult concepts, and construct understanding in a way that aligns with their cognitive development [5]. From intellectual perspective, this approach supports the management of intrinsic and extraneous cognitive load, allowing students to build mental models more effectively before engaging in complex problem solving. In this model, content is accessed independently outside of class, while classroom time is reserved for higher-order learning, collaborative work, and instructor-guided clarification [6], [7].

By shifting direct instruction outside the classroom and reserving in-class time for active learning, problem solving, and class activities, the flipped model offers several well-documented advantages: it promotes deeper conceptual understanding, increases student engagement, and allows instructors to dedicate class time to higher-order thinking [2], [4]. These outcomes are closely aligned with key engineering education goals, including the development of problem-solving skills and the ability to acquire and apply new knowledge effectively. However, despite these strengths, the model also presents notable challenges. Redesigning a course for flipped delivery is time-intensive, and not all students consistently complete pre-class activities; some may even resist the format due to unfamiliarity or preference for traditional lectures [8], [9].

To navigate these limitations while still leveraging the benefits of the flipped model, instructors can adopt a partial or hybrid approach—flipping selected components of the course rather than the entire curriculum [10]. In subjects such as thermodynamics, many foundational topics lend themselves naturally to pre-class exploration, enabling students to arrive better prepared for rigorous in-class problem solving. Moreover, the substantial workload associated with course redesign can be significantly reduced through the use of artificial intelligence. AI tools can efficiently generate introductory content, visual explanations, and supplemental resources, allowing instructors to focus their efforts on crafting meaningful in-class activities and providing targeted guidance [11], [12]. In this way, AI becomes a practical and pedagogically aligned solution for enhancing the flipped classroom while mitigating its most common barriers, while also supporting students' ability to engage in analytical reasoning and model-based thinking.

Technological advancements have significantly expanded access to information by enabling students to engage with vast bodies of knowledge and global learning resources [13]. Within this evolving landscape, integrating artificial intelligence (AI) into coursework offers an important pedagogical opportunity: AI can function as both a learning partner connecting students to a wide variety of information available online and as a catalyst for deeper inquiry [14].

Students are no longer limited to textbooks or physical library materials; instead, they gain access to dynamic, multimodal, and real-time information sources. This results in changing student behavior where majority of students are already using AI tools in some form, regardless of formal instructional guidance, redefining traditional classroom roles by moving instructors away from being the sole source of knowledge and toward facilitating active, inquiry-driven learning experiences [15]. However, in the absence of structured guidance, students may become vulnerable to misinformation, incomplete reasoning, or AI-generated inaccuracies (commonly referred to as hallucinations). A more effective approach is to intentionally integrate AI into coursework through instructor-designed activities and prompts. By doing so, instructors can guide students toward productive and critical use of AI, rather than leaving them to navigate these tools independently. Adding a new dimension of engineering education: the need to evaluate the validity and reliability of information sources reinforcing skills related to engineering judgment, verification of results, and ethical use of technology—competencies that align with professional expectations in engineering practice.

Additionally, technological fluency of newer generations makes these pedagogical shifts even more essential. Today's students are more comfortable with digital tools, online platforms, and interactive technologies than prior cohorts. As such, institutions and instructors must adapt their teaching practices to align with these new norms, which include embracing technology-mediated course delivery. Although a vast amount of online educational content exists, it presents two limitations: (1) it is rarely tailored to the specific goals, outcomes, or thematic focus of an instructor's course, and (2) it often lacks meaningful feedback mechanisms. AI has the potential to bridge this gap. It allows instructors to generate high-quality, course-specific learning materials that match their pedagogical intentions, while simultaneously providing real-time feedback—thereby enhancing the value and distinctiveness of university education.

As AI tools become more integrated into learning environments, there is increasing value in designing problems, examples, and supporting materials that emphasize interpretation, critical thinking, and engagement rather than procedural computation alone. Consequently, there will be a growing need to reconsider conventional textbooks and teaching resources to better align with evolving technological capabilities, disciplinary expectations, and student learning needs.

Another important consideration with the usage of AI is equitable access. Many AI tools require paid registration, which may create disparities among students based on financial resources. To address this concern, the AI-based activities presented in this work are intentionally developed using widely accessible, free tools—specifically ChatGPT, Copilot, and Gemini. This approach helps ensure that all students, regardless of economic background, can engage with the material on equal footing. It also supports inclusive pedagogy by reducing barriers to participation and aligns with broader educational goals of accessibility and equity in engineering education.

In the following sections, strategies that can be employed to make course content more engaging and technology-driven in the context of inverted learning are discussed.

1) Inquiry-Based Questions

AI enables the design of inquiry-based learning tasks that encourage students to explore authentic problems. For example, instead of showing students a table of atmospheric pressures at selected locations from the textbook that was published years ago. Students may be asked to use online AI tools to determine atmospheric pressures at selected global locations of their interest and plot these values against altitude. Such an exercise not only highlights the inverse relationship between pressure and elevation but also produces inherently unique responses, thus reducing the risk of plagiarism. As an example, Figure 1 illustrates an AI-generated plot based on a student's query of finding and plotting atmospheric pressure versus altitude.

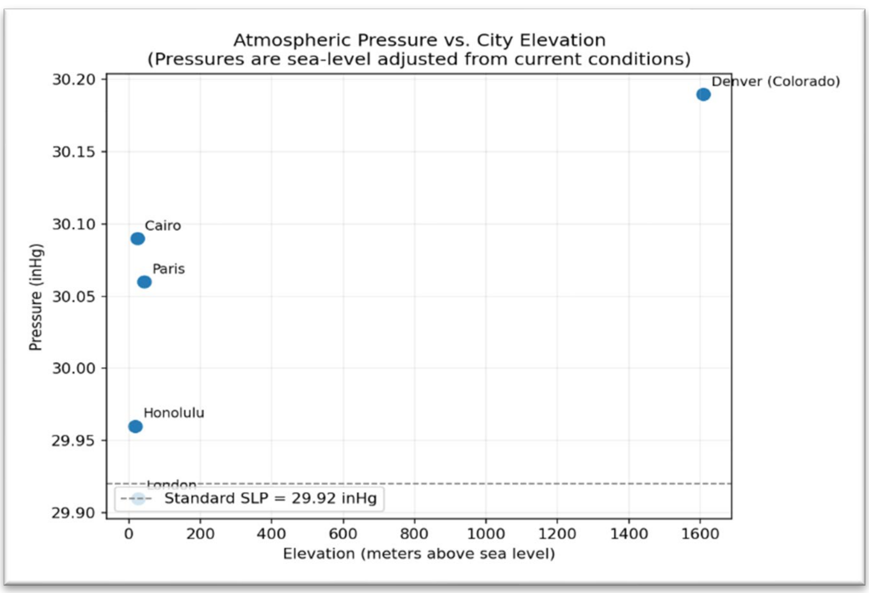

Figure 1: Atmospheric pressure vs City Elevation. Copilot was used. Prompt given plot current atmospheric pressure (mmHg) for the following cities.

Further, instructors can select some plots during class discussions, strengthening engagement and creating a classroom culture where student contributions carry intellectual weight. It also invites students to interact with real-time scientific data, making the learning experience more relevant and connected to global phenomena.

However, the software-generated plot initially relied on sea-level–adjusted pressures rather than true station pressures, revealing a conceptual disconnect. This creates a meaningful instructional moment: students require guidance to understand why the results appear inconsistent and what "sea-level adjustment" means in the context of thermodynamics. The example underscores the complementary relationship between AI and instruction—AI can accelerate information retrieval and visualization, but the instructor remains essential for contextualization, conceptual accuracy, and refinement. Through iterative guidance, students can ultimately generate a scientifically accurate plot that captures the inverse relationship between atmospheric pressure and elevation, as shown in Figure 2.

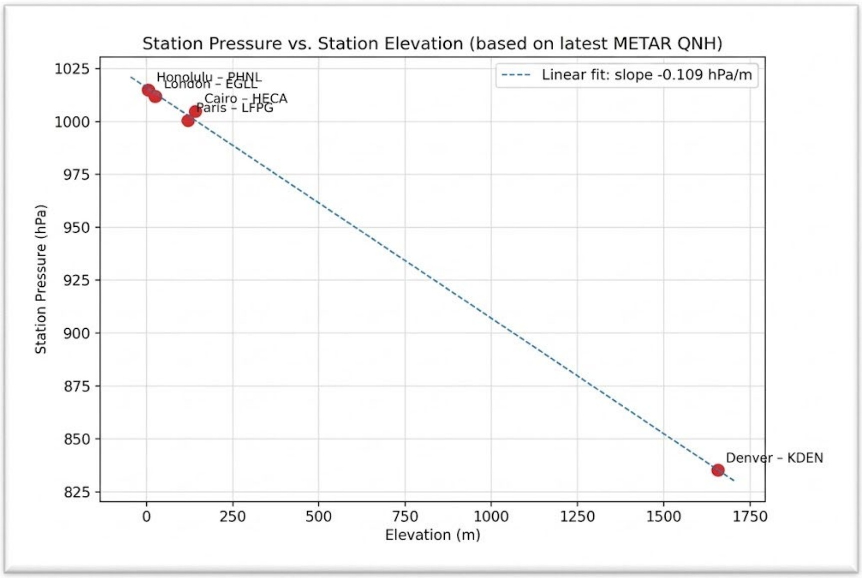

Figure 2: Pressure vs Elevation for four different cities. Prompts given use station pressure, etc.

Whether conducted in class or assigned as pre-class work, this activity incorporates some key elements of effective learning, including active engagement, curiosity, and real-world relevance. Similar problems can be developed to explore gas behavior using alternative models, such as the ideal gas equation or the van der Waals equation.

2) <u>Communication and Collaboration</u>

Beyond data analysis, AI tools support communication and collaboration by providing platforms that allow students to interact with peers and experts globally. Collaborative digital tasks—such as co-designing AI-generated visualizations of pollutant effects (e.g., NOx, unburned hydrocarbons, carbon monoxide)—strengthen teamwork, scientific reasoning, and visual literacy. Figure 3 shows two AI-generated images of the environmental impact of pollution.

Figure 3: Impacts of pollution. Generated iteratively using ChatGPT. Prompts include: Create an image displaying environmental impacts of pollution and then add focused points like acid rain, water toxicity, global warming, etc.

While the images effectively identify the major challenges associated with pollution, it also presents a substantial amount of information that students may find difficult to interpret without guided support. It provides an engaging platform for the instructor to highlight important aspects and carry out meaningful in-class discussions. This further reinforces the indispensable role of the instructor, who not only clarifies the technical details embedded within such visualizations but also helps students adapt these images to highlight targeted dimensions—such as specific effects on human health or agricultural systems. By doing so, instructors enable learners to connect abstract technical content with broader societal and environmental concerns. Also, these images are not labeled, providing the instructor with the opportunity to ask students to label, testing their knowledge, and opening the door to image-based assessment. Figure 4 shows the labeled image highlighting how NO_x should relate to power plants, while UHCs relate to automobiles and jets.

Figure 4: Impact of Pollution Labeled. Prompts include: Label NOx, smog, move planet to right etc.

This type of Image generation exercise can be easily assigned as an at-home task, allowing students to generate and explore the visualization independently before class. The instructor can then unpack the technical nuances during the following session, thereby modeling an inverted (flipped) learning approach in which foundational exploration occurs at home and higher-order sense-making occurs in class. Moreover, the instructor can extend this learning through focused image refinement, prompting students to analyze a specific topic (e.g., impacts of NOx emissions and explore strategies for their mitigation). Figure 5 synthesizes these targeted explanations, illustrating how instructor-guided inquiries complement AI-generated materials to deepen student understanding.

Figure 5: NO_x health related issues. Generated iteratively using Gemini. Prompt includes: Create a picture showing NOx pollution, use car as pollutant, include health effects, make more suitable for research paper, etc.

3) Instructional Support Media

The flipped classroom model can be an ideal way to deal with introductory topics. Creating instructional support resources, for example a polished video requires a significant amount of time, editing, and effort to produce. Many course topics are introductory or foundational in nature; while instructors may not wish to invest substantial time in producing videos for such topics, AI, however, offers a rapid and efficient means of converting instructor expertise into a presentable video format even for such introductory topics. It can generate high-quality, audience-specific content with minimal effort. Figure 6 provides a collage of AI-generated video snaps serving as an introduction to thermodynamics tailored specifically to biomedical engineering students, incorporating domain-relevant examples that enhance disciplinary resonance.

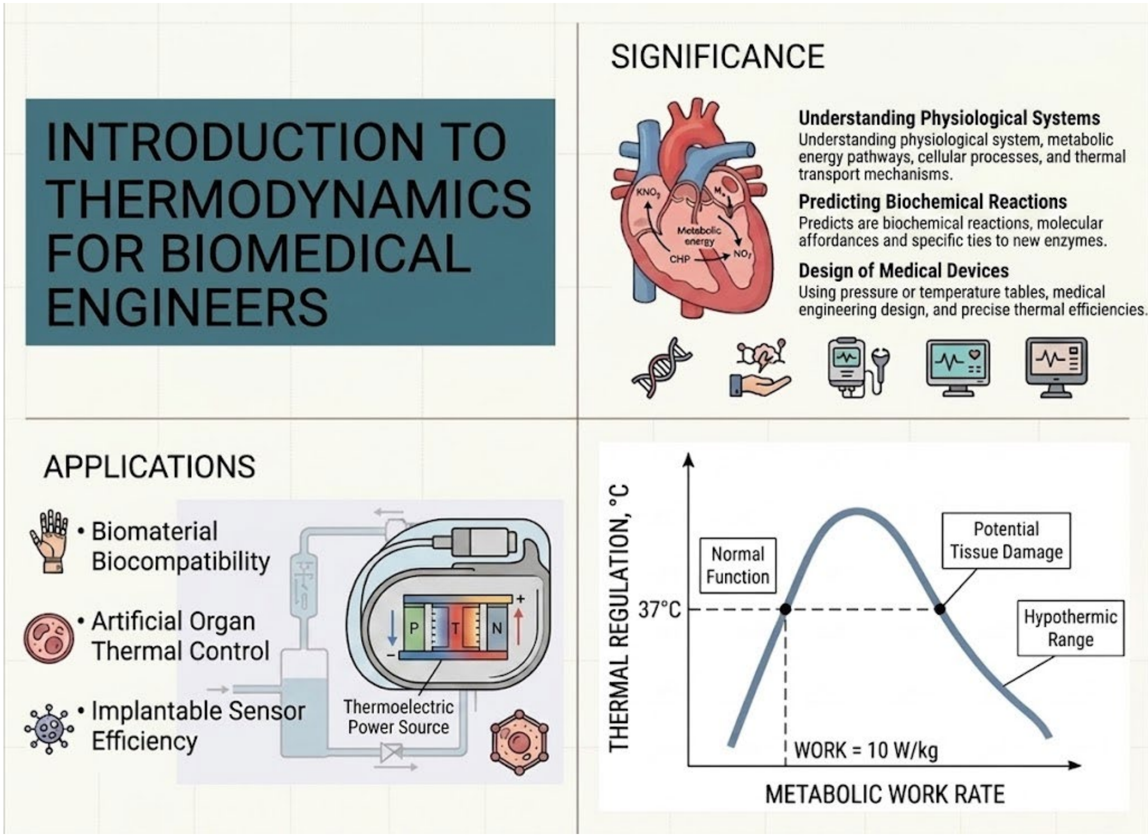

Figure 6: Snaps from video featuring introduction to thermodynamics tailored for biomedical engineering majors. Slides were generated by copilot while pictory.al was used to convert it into the video.

These videos (i.e., can be animated slides, voice-over narrations, etc) can then be linked to formative assessment. Once students complete an assigned video, they can respond to an accompanying questionnaire designed to evaluate comprehension. This ensures that all students—regardless of engagement or attention levels during live instruction—begin class with a shared baseline understanding.

A sample questionnaire associated with this introductory video is presented in Figure 7. Since the questionnaire is based strictly on the data provided, there is no opportunity for inaccuracy, resulting in perfect scores and appraised by many students. Collectively, the flipped classroom model, when supported by AI-generated instructional materials and targeted assessments, promotes self-paced learning, strengthens student–instructor connection, and ensures that all students are equipped to participate meaningfully in higher-order classroom activities.

3. Which of the following is an example of an open thermodynamic system in biomedical engineering?

A. A sealed blood sample vial

B. A thermos flask

C. A human lung during breathing

D. A perfectly insulated box

Correct answer: C

4. Which form of energy is primarily responsible for maintaining body temperature?

A. Kinetic energy

B. Electrical energy

C. Thermal energy

D. Nuclear energy

Correct answer: C

Figure 7: AI-generated multiple-choice questions tailored to Biomedical Engineering. Generated by copilot completely based on the instructors' input and topics discussed within the video.

4) Supporting Computational Problem Solving

In addition to supporting conceptual understanding, AI-enhanced flipped-classroom strategies can be effectively combined to address the challenges of calculation-intensive problem solving. Integrating AI into the curriculum enabled me to address questions previously omitted due to time constraints. I was able to assign the computationally intensive problems as homework that I used to bypass, allowing for a more rigorous exploration of the subject.

AI tools allowed students to focus on interpreting and applying physical concepts rather than becoming overwhelmed by algebraic manipulation, spreadsheet skills, or repetitive numerical procedures. This is particularly valuable in thermodynamics, where textbooks frequently include data-driven problems—such as plotting thermodynamic properties or solving multi-step equations—that instructors may overlook due to time constraints or uncertainty about students' computational readiness. By offloading routine or time-consuming calculations to AI, instructors can reallocate class time toward higher-order reasoning, conceptual discussion, and the interpretation of results.

For example, after completing the topic of conservation of mass principle, the instructor can assign an out-of-class task that requires generating a plot of tank volume as a function of time. In this case, AI was instructed to create a plot (Figure 8) using the following data:

(1) An initial volume of 100,000 gallons, and

(2) A volumetric flow rate defined by 5000 e^{-t/20}, with t in days.

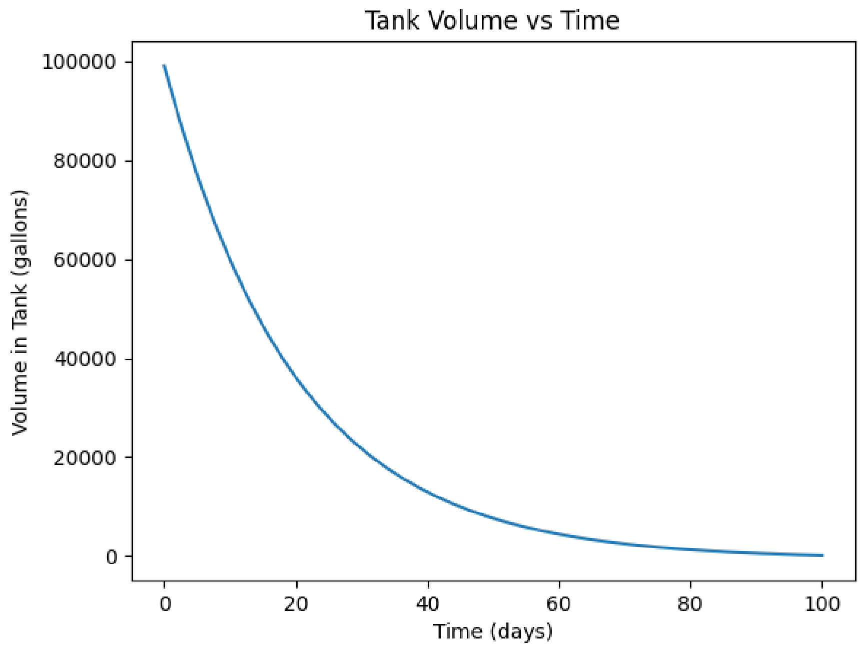

Figure 8: Tank volume vs time (Constraint and Well defined). ChatGPT was used. It will be difficult for some students to solve for volumetric flowrate and generate a plot within short period of time.

Not only does the plot clearly display a relationship between two variables, but it also doesn't require students to know how to solve and plot exponent equations. Along with the visualization, AI is also asked to produce a step-by-step explanation of how the equation was solved, providing an optional enrichment resource for students who wish to understand the underlying mathematical method.

A second example involving the analysis of deviations of water vapor from ideal gas behavior is also presented. Students were asked to examine the changes in specific volume of water vapor at 15 MPa across temperatures from 350°C to 600°C, then quantify the percent error introduced by using the ideal-gas approximation. The resulting AI-generated plot, shown in Figure 9, reveals trends that would otherwise require significant spreadsheet proficiency. Instead of spending hours manipulating data tables in Excel, students can immediately explore how ideal-gas errors diminish with temperature. This allows them to concentrate on the physical meaning of the deviations rather than the mechanics of producing the plot.

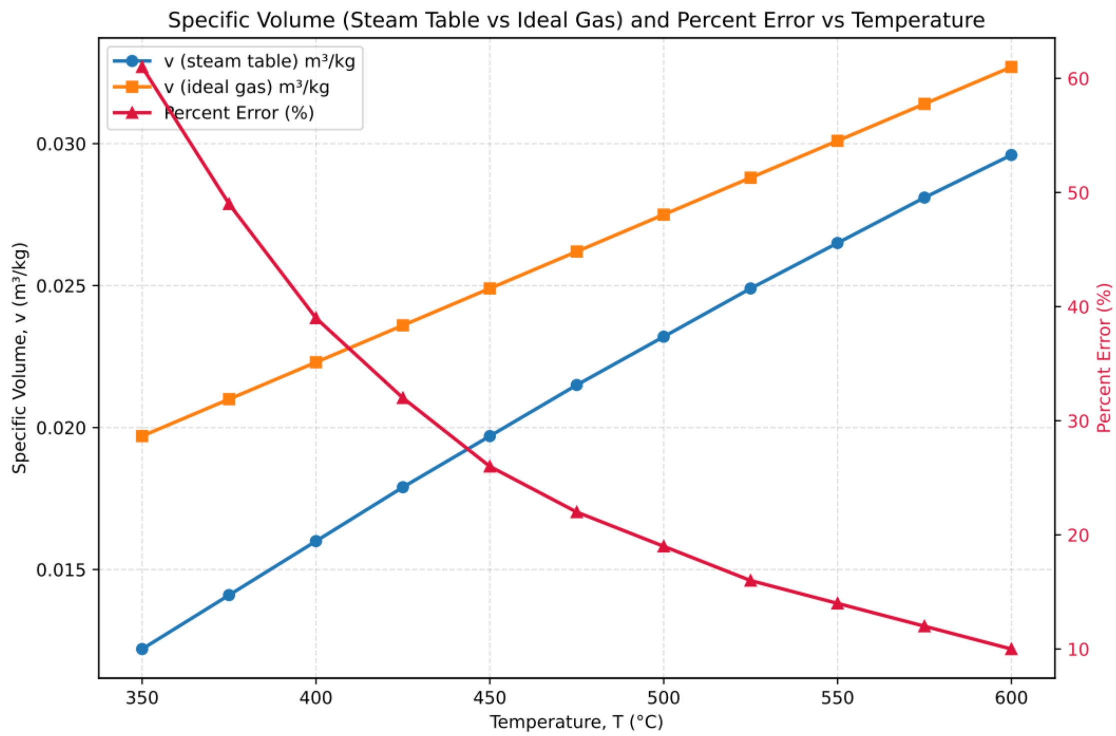

Figure 9: Specific volume of water vs temperature. Students were able to plot and analyze their own graphs as homework without getting into the spreadsheets, etc.

Viewed together, these examples illustrate how AI transforms labor-intensive tasks traditionally into opportunities for deeper learning. By reducing the computational burden, AI enables students to engage more fully with the scientific principles at stake—precisely the type of conceptual enrichment that the flipped classroom is designed to promote.

5) Addressing Potential Drawbacks of AI-Assisted Calculations

a) Mathematical Skills and Repetitive Calculations

The use of AI tools in student problem solving is often accompanied by concerns related to diminished critical thinking, potential inaccuracies, and the development of mathematical deficiencies. While these concerns are reasonable, their impact depends strongly on how and where AI is integrated within the curriculum. It is important to distinguish between foundational mathematical skills that students are expected to have mastered prior to a given course and higher-level disciplinary learning objectives. When AI is applied selectively to routine or prerequisite computations, it can serve as a support mechanism rather than a replacement for critical thinking. This perspective is supported by prior research indicating that appropriately designed technology-enhanced learning environments can reduce extraneous cognitive load, enabling students to focus more effectively on conceptual understanding rather than procedural effort [16].

For instance, the example associated with Figure 8 involves evaluating an integral containing an exponential term. Such mathematical operations are typically covered in earlier coursework (e.g., calculus sequences completed by the second year of an engineering program) and are not central learning objectives in a thermodynamics course. In this context, requiring students to manually perform these integrations may shift focus away from core thermodynamic concepts. Therefore, tasks of this nature represent appropriate opportunities for AI-assisted computation, allowing students to concentrate on interpreting physical meaning rather than executing procedural mathematics.

At the same time, instructor oversight remains essential to ensure both accuracy and pedagogical effectiveness. AI-generated solutions are not inherently reliable and may produce incorrect or misleading results, particularly when problem statements are ambiguous or insufficiently constrained. An example of such an AI response is shown in Figure 10.

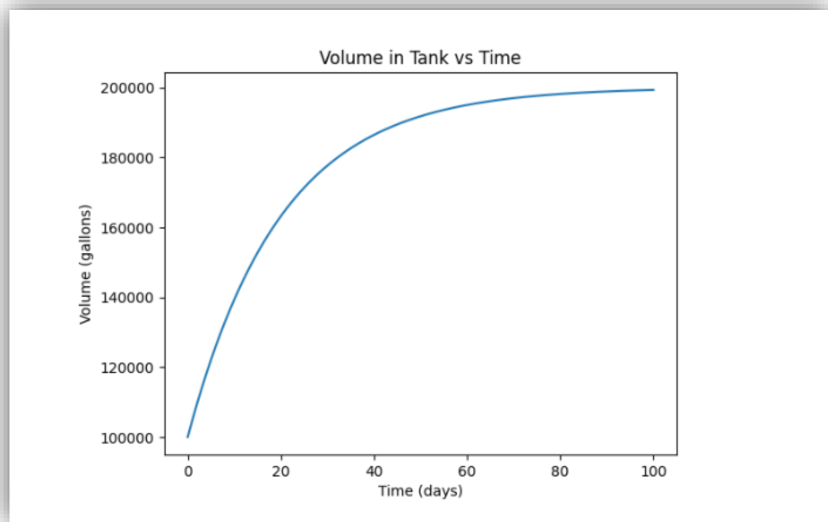

Figure 10: Tank volume vs time (unconstraint & not completely defined). ChatGPT was used. In the second iteration it was identified the case is outflow not inflow as initially assumed.

This example highlights the importance of carefully designing and validating AI-supported assignments prior to their deployment. Instructors must test prompts, verify outputs, and anticipate potential errors to ensure that AI serves as a constructive educational tool. In this framework, AI does not replace instructor responsibility but rather increases the need for deliberate instructional design and oversight. Prior research also emphasizes that the effectiveness of AI in flipped learning environments depends heavily on instructor guidance and careful integration, rather than unrestricted use [17].

A second consideration involves repetitive and time-intensive computations. In the example of Figure 9, students are required to evaluate properties at multiple temperature points—often involving repetitive use of thermodynamic tables or equations. They must determine values at eleven different temperatures, followed by repeated application of the ideal gas equation and subsequent graph construction, can be laborious and may contribute little to conceptual understanding. These steps are primarily procedural and can detract from more meaningful engagement with the material. Previous studies have also indicated improved learning efficiency by managing cognitive load and reallocating effort toward higher-order thinking task [18].

By leveraging AI to automate such repetitive calculations and generate plots efficiently, students can redirect their effort toward analyzing trends, evaluating model assumptions, and interpreting deviations from idealized behavior. In this way, AI reduces time spent on low-value procedural tasks while preserving—and potentially enhancing—opportunities for critical thinking and conceptual reasoning.

Overall, the effective use of AI in engineering education does not eliminate rigor but redistributes it. When implemented with intentional boundaries and active instructor oversight, AI can mitigate computational barriers while maintaining a strong emphasis on analytical depth and conceptual understanding.

b) Redesigning Problems for AI based course content

A common criticism of AI-based computational tools is that they may hinder the development of student problem-solving and critical thinking skills by promoting passive information consumption and reducing cognitive engagement. While these concerns are valid, they are often a consequence of *how* AI is used rather than an inherent limitation of the technology itself. In many cases, traditional problems are not designed to leverage AI effectively, and when such problems are directly submitted to AI systems, the resulting interaction bypasses meaningful student engagement. To fully evaluate the educational potential of AI-based tools, problems must be intentionally designed for interactive, student-centered engagement rather than direct solution retrieval.

Consider the following simple traditional thermodynamic problems:

"A piston–cylinder device initially contains 0.4 m^3 of air at 100 kPa and 80°C. The air is now compressed to 0.1 m^3 in such a way that the temperature inside the cylinder remains constant. Determine the work done during this process.

When this problem is directly entered into an AI system, the tool typically extracts the given values, applies to the appropriate formula, and produces a correct numerical answer with minimal cognitive demand placed on the student. In this format, the student's role is indeed reduced to passive consumption, limiting opportunities for conceptual reasoning or problem-solving skill development. To address this limitation, the same problem can be restructured into an AI-supported interactive exercise (i.e., python language, jupyter notebook as compiler, both free version). In this approach, AI is used to generate a guided computational program that engages students at each stage of the solution process as shown in Figures 11(a)(b)(c). Rather than providing all values upfront, the system prompts students to input relevant parameters, identify governing relationships, and make decisions throughout the solution process.

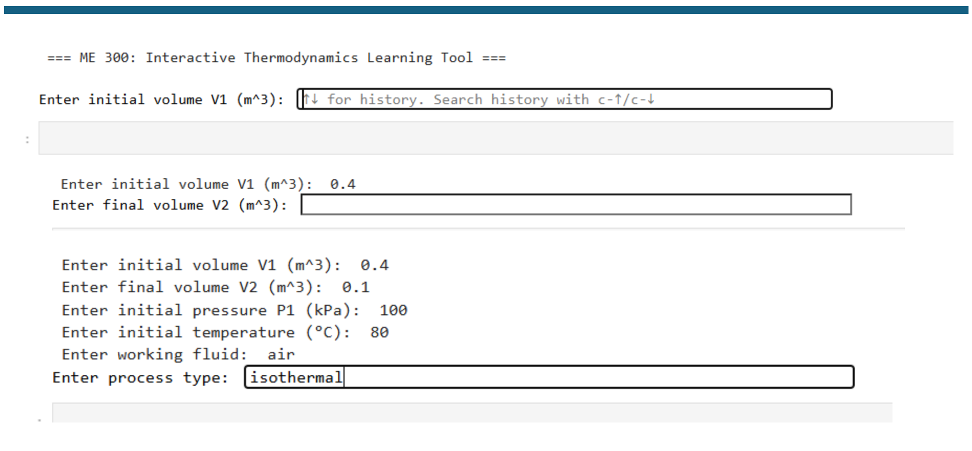

Figure 11(a): Question redesigned for better student engagement. Copilot was used.

In this redesigned format, students are required to actively participate in the problem-solving sequence. The program is structured to validate inputs in real time; incorrect entries trigger prompts for revision along with targeted hints to guide student thinking. Once the necessary parameters are correctly identified, students are asked to select or enter the appropriate governing equation for an isothermal process. This step can be implemented through open-ended input or structured formats such as MCQ's, depending on the desired level of scaffolding.

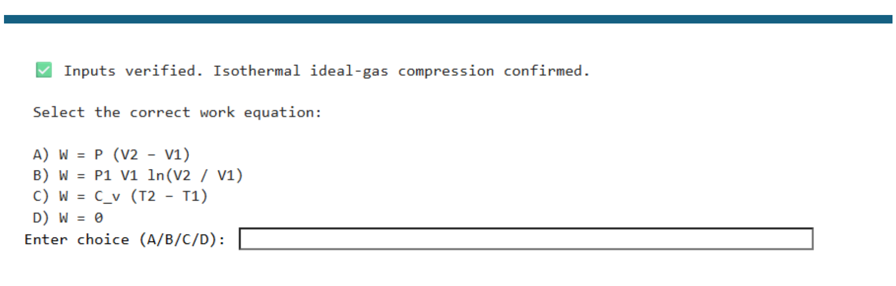

Figure 11(b): Student was asked to select the correct equations.

Students are then required to perform the work calculation manually and submit their result. The system verifies the response and provides immediate feedback, including identification of common errors such as incorrect sign conventions. Following the calculation phase, the program generates a pressure–volume (P–V) plot, allowing students to visualize the process. Students can further explore the system by modifying input parameters and observing how the curve changes, promoting deeper understanding of thermodynamic relationships. After completing the computational and exploratory components, students can be assessed using conceptual questions that prove their understanding of the underlying physical principles.

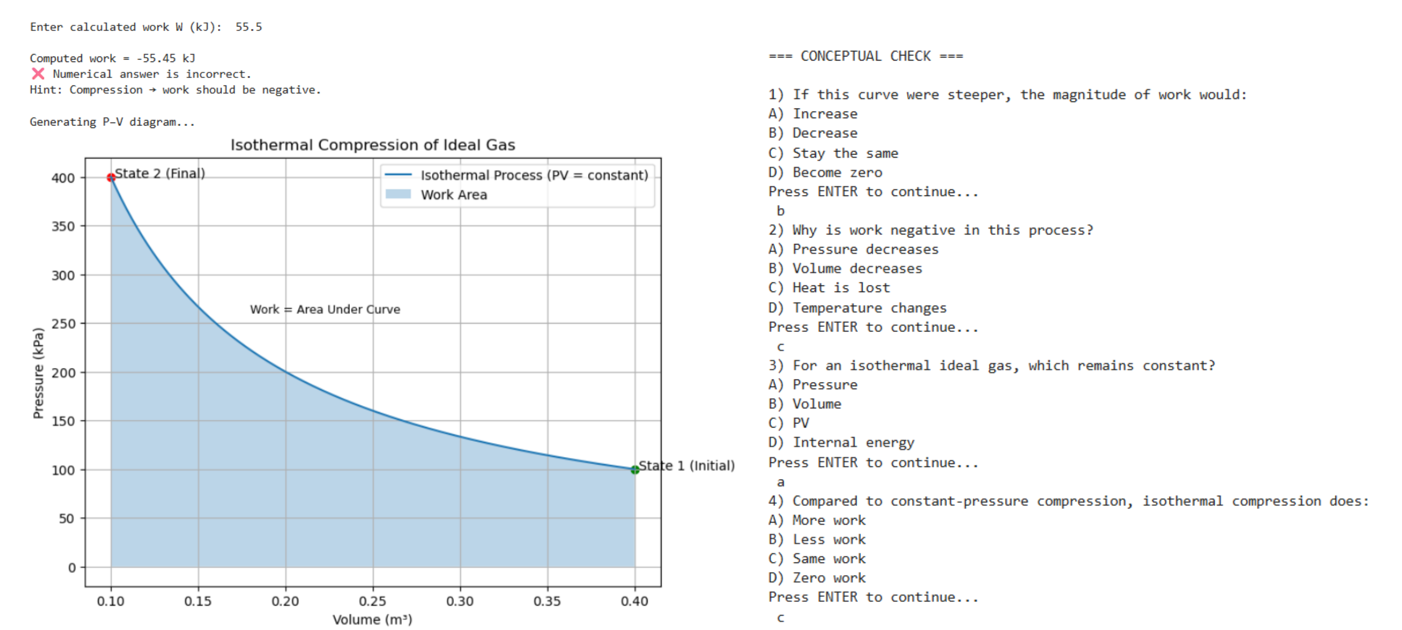

Figure 11(c): Student generated plot and conceptual questions.

This example illustrates how a conventional problem can be transformed into an interactive learning experience that is fundamentally dependent on student input and reasoning rather than passive solution retrieval. An additional advantage of AI-based problem design is the ability to capture detailed student interaction data. When integrated into learning management systems such as Canvas, these tools can track metrics such as the number of attempts, types of errors, and time spent on each step. Such data provides valuable formative assessment opportunities. At the instructor level, it can highlight specific topics or concepts that require additional emphasis during in-class instruction. At the student level, it enables the identification of individuals who may be struggling with some specific aspects of the material, allowing for targeted intervention and personalized support. This aligns with broader goals in engineering education related to adaptive learning, continuous assessment, and data-informed instruction.

To evaluate the effectiveness of this approach, data were collected from similar problems administered in midterm assessments over the past three years. These problems required students to compute work and generate P–V diagrams for varying process parameters (e.g., different polytropic indices). The results, summarized in Figure 12, show an increase in student response accuracy from 65% in 2023 to 82% in 2025, following the introduction of AI-supported, interactive problem design in 2025. The overall trend suggests a notable improvement in student performance after the implementation of structured AI-based exercise.

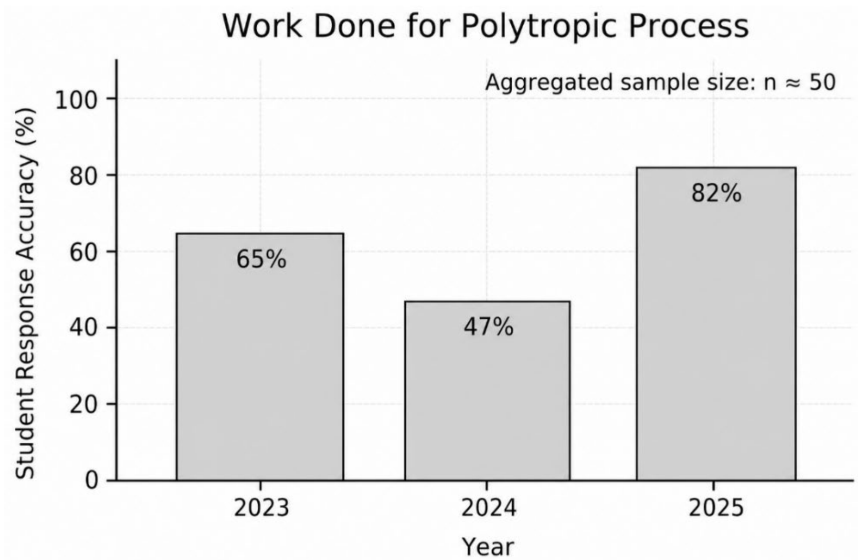

Figure 12: Student response accuracy for a polytropic process problem across three academic years (2023–2025), with an aggregated sample size of approximately n ≈ 50. AI based exercise was only given in 2025.

c) ***Designing Supplementary Aid Material***

The flipped classroom model is also well-suited for some problem-solving tasks that are non-linear and conceptually layered. By engaging with foundational content before class, students arrive better prepared for in-depth problem-solving during instructional time. For instance, when introducing students to the use of steam tables, instructors can provide a short pre-class video (Figure 13) or slide presentation demonstrating how to locate key thermodynamic properties—such as internal energy—at specified states. Classroom time can then be dedicated to applying these principles to more complex problems, enabling instructors to cover additional material while maintaining a highly engaging, interactive environment.

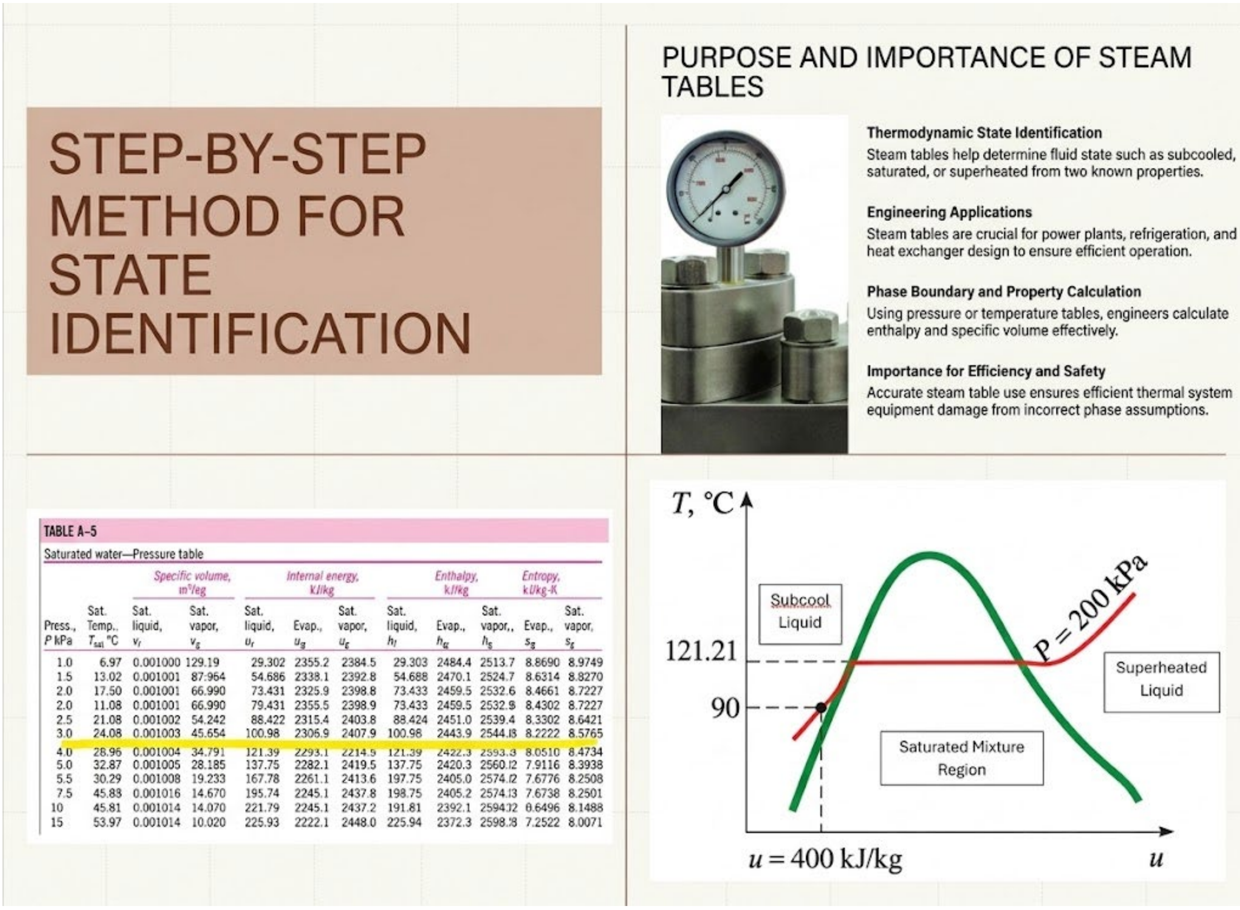

Figure 13: Snaps from the instructional video demonstrating how to extract values from a steam table.

Students were required to watch the video, get familiar with the pseudo-code (Figure 14) and complete one exercise prior to attending class as homework. This approach most benefit students who are underprepared or falling behind—often the same students who turn to online platforms such as YouTube for supplementary explanations. When instructors create customized AI-supported content, they not only elevate the quality and relevance of available learning materials but also strengthen the pedagogical connection between themselves and their students.

```
INPUT: Any two independent properties of water (e.g., T, P, h, x, v, etc.)

BEGIN

1. Identify known properties
   Store given values (T, P, h, x, etc.)

2. Select appropriate steam table
   IF P is known THEN
       Use saturation table at given P
   ELSE IF T is known THEN
       Use saturation table at given T
   ENDIF

3. Determine phase

   IF quality (x) is given THEN
       Phase = Saturated mixture

   ELSE
       Find saturation properties at given T or P:
           Tsat or Psat
           hf, hg (or vf, vg)

       IF T < Tsat (or P > Psat) THEN
           Phase = Compressed (subcooled) liquid

       ELSE IF T = Tsat (or P = Psat) THEN
           Phase = Saturated mixture

       ELSE IF T > Tsat (or P < Psat) THEN
           Phase = Superheated vapor
       ENDIF
   ENDIF

4. Calculate missing properties

   IF Phase = Saturated mixture THEN
       Use quality relations:
           h = hf + x(hg - hf)
           v = vf + x(vg - vf)
           (same for u, s if needed)

   ELSE IF Phase = Compressed liquid THEN
       Approximate properties using saturated liquid values at given T:
           h = hf @ T
           v = vf @ T

   ELSE IF Phase = Superheated vapor THEN
```

Figure 14: Pseudocode: Determining Phase & Properties Using Steam Tables. Generated by ChatGPT.

To evaluate the effectiveness of this material, two key metrics were considered: (1) Number of lecture hours required to complete this topic, and (2) the frequency with which students sought instructor assistance completing homework. These metrics were selected to capture both instructional efficiency and student dependency on external support. Figure 15 indicates a reduction in instructional time from 6 to 5 sessions alongside a decrease in student help-seeking rates from 30% to 20% after implementing AI-supported activities. Further, increased in-class participation was observed, with more students actively engaging in discussions and giving answers to in-class problems.

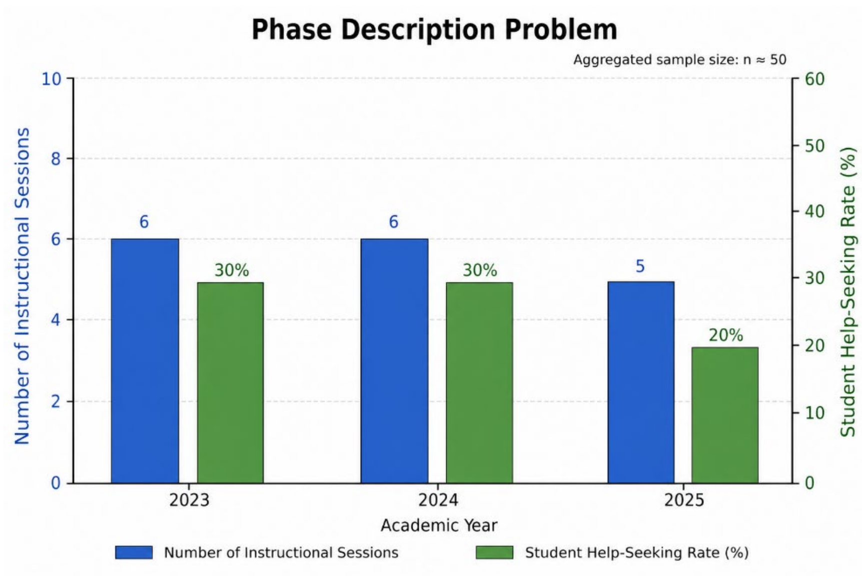

Figure 15: Number of instructional sessions and student help-seeking rate (%) for the phase description problem across academic years (2023–2025)

These improvements indicates that when AI is used to promote active engagement—rather than passive solution retrieval—it can enhance both computational accuracy and conceptual understanding. However, it is important to note that these findings are preliminary. Additional data collection, controlled comparisons, and broader implementation across multiple topics will be necessary to establish statistically significant correlations between AI-assisted problem design and student learning outcomes.

6) <u>Laboratory Simulations</u>

Developing a strong understanding of pressure measurement using manometers is a foundational skill in thermal-fluid sciences. While such concepts were traditionally reinforced through in-person laboratory sessions, advances in AI now make it possible to create rich, interactive virtual laboratory experiences that supplement or partially replace physical labs. Instructors can assign these virtual simulations as homework or as pre-class activities, allowing students to explore the relationships between absolute and gauge pressure at their own pace. Within these simulations, students can manipulate both open and closed-end (vacuum) manometers to observe how fluid-column height responds to changes in applied pressure. Additional layers of learning—such as comparing why mercury columns exhibit smaller height changes than water columns under identical pressure differences—can be incorporated to deepen conceptual understanding. Figure 16 illustrates several elements of such an AI-generated simulation.

Figure 16: Screenshots of Lab Simulation about using manometers and measuring pressure

Notably, the visualization shown was produced in a single iteration and has not yet been refined; however, even at this preliminary stage, it demonstrates the potential of AI to generate meaningful instructional tools. With further customization, instructors can enhance clarity, add explanatory annotations, and tailor the visual environment to specific course outcomes. At its core, though, the simulation already provides an engaging and accessible platform through which students can explore manometry principles, thereby strengthening both conceptual comprehension and readiness for more advanced thermal-fluid topics.

7) <u>Unit Conversion & Crib Sheets</u>

Additionally, AI-supported materials can be used to offload foundational topics—such as unit conversion—into an online, self-paced learning module, thereby allowing classroom time to focus on numerical problem-solving and conceptual application. In my course, for example, I asked students to review a short AI-generated explanation of essential unit conversions (e.g., MPa to psi) and then prepare a printed reference sheet using any AI tool of their choice. The results were highly encouraging: students arrived with well-organized crib sheets, demonstrated stronger comprehension, and were able to solve most numerical problems with greater confidence. This approach not only promotes responsibility and ownership of learning but also makes the act of creating a personalized crib sheet more engaging and meaningful. Figure 17 shows an AI-generated image of formulas for the crib sheet. Additionally, it can also generate a quick plot showing the correlation between those temperatures and be readily available for students to solve any conversion problems.

- Celsius ↔ Fahrenheit:

$$T(^{\circ}F) = \frac{9}{5}T(^{\circ}C) + 32$$

$$T(^{\circ}C) = \frac{5}{9}(T(^{\circ}F) - 32)$$

- Celsius ↔ Kelvin:

$$T(K) = T(^{\circ}C) + 273.15$$

$$T(^{\circ}C) = T(K) - 273.15$$

- Fahrenheit ↔ Rankine:

$$T(^{\circ}R) = T(^{\circ}F) + 459.67$$

$$T(^{\circ}F) = T(^{\circ}R) - 459.67$$

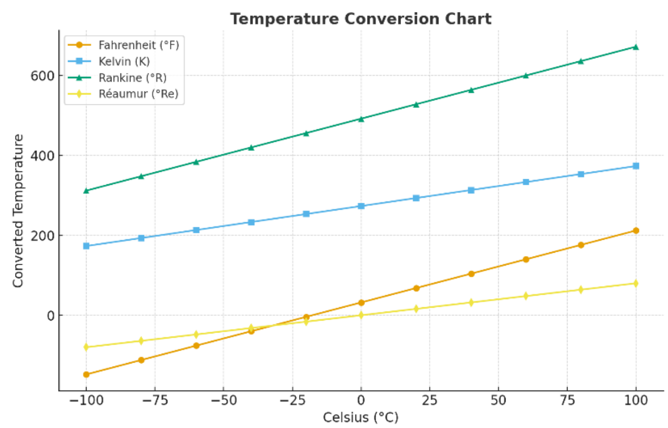

Figure 17: Formulas and plot for crib sheet

A related benefit is the reinforcement of important constants. By instructing students to bring and routinely use their constant sheets during class, they encounter these values repeatedly supporting gradual internalization and long-term recall. In this way, AI-enabled preparatory tasks complement in-class instruction, helping students build both accuracy and fluency while freeing classroom time for deeper analytical work.

8) <u>Supplementary Material for Underprepared Students</u>

AI can also serve as a powerful tool for generating individualized practice materials for students who are struggling. Traditionally, instructors have relied on assigning additional textbook problems or supplemental readings to support these learners; however, such materials are rarely tailored to a student's specific misconceptions or learning needs. AI offers a more targeted alternative. For instance, when one of my students had difficulty formulating first-law energy balance equations, I was able to generate customized images (Figure 18) illustrating various energy-exchange scenarios. These visuals enabled me to design schematic questions that directly addressed the students' conceptual gaps.

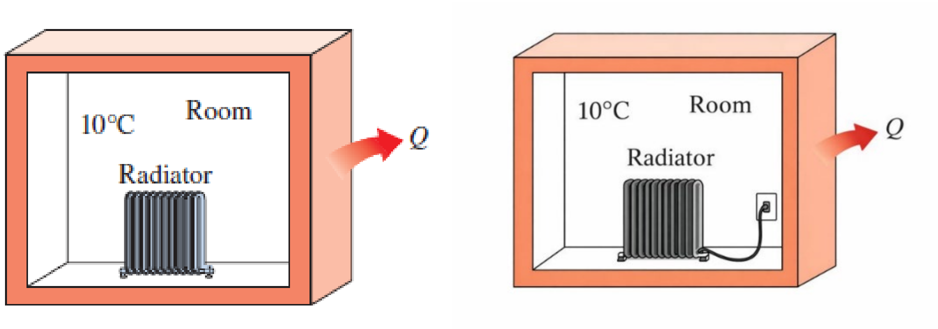

Figure 18: Images generated to improve understanding of energy-balanced equations. ChatGPT was used. It highlights difference in energy balance equation due to the use of electricity in second figure.

It is important to note that producing pedagogically meaningful images with AI may require some iteration. Initial outputs often prioritize aesthetic appeal over engineering substance, as demonstrated when my first request for a "radiator in a room" yielded a visually striking but scientifically superficial depiction (Figure 19). With a small amount of refinement, however, the AI system began to generate thermodynamically accurate representations aligned with course objectives. This adaptability illustrates one of AI's greatest strengths—its ability to progressively "learn" the instructor's preferred style, terminology, and conceptual emphasis.

Figure 19: What AI thinks generally.

Ultimately, this capacity for customization reinforces the broader argument that AI will reshape contemporary teaching practices. By enabling instructors to create bespoke learning aids quickly and efficiently, AI enhances instructional responsiveness and supports more personalized learning trajectories. Figure 19 illustrates the initial image produced by the AI module, marking the starting point from which more discipline-specific refinements were developed.

9) Virtual Tutor for Derivations

Finally, AI can also function as a virtual tutor, particularly for guiding students through mathematical or conceptual derivations. Although thermodynamics contains relatively few derivations—and many instructors consider them straightforward enough to cover briefly in class—they can still pose difficulties for students who need additional time and structure to internalize the steps. Assigning these derivations as a pre-class or homework activity allows students to engage with them at their own pace. Figures 20 and 21 illustrate an example of an AI-supported tutoring script that leads students through the derivation of Fourier's law of conduction. As seen in the dialogue, the explanations are detailed, sequential, and largely self-explanatory, requiring only minimal instructor intervention. This makes such AI-generated tutoring sequences highly compatible with a flipped-learning framework, where foundational comprehension is developed independently and classroom time is reserved for deeper problem-solving and conceptual discussion.

2. One-dimensional conduction model

Consider a **plane wall**:

- Area A
- Thickness dx
- Temperature varies only in the x-direction
- Steady-state conduction
- No internal heat generation

Let:

- $T(x)$ be the temperature distribution
- q be the heat transfer rate

3. Proportionality assumptions

From experiments, the heat transfer rate is found to be proportional to:

- Area:

$$q \propto A$$

- Temperature difference:

$$q \propto \Delta T$$

- Inversely proportional to thickness:

$$q \propto \frac{1}{dx}$$

Combining:

$$q \propto A \frac{\Delta T}{dx}$$

Figure 20: Virtual tutor explaining the model and assumptions. Developed for the students having difficulty in understanding the Fourier law basics.

4. Differential form

As $dx \to 0$, the temperature difference becomes a derivative:

$$\frac{\Delta T}{dx} \to \frac{dT}{dx}$$

So:

$$q \propto A\frac{dT}{dx}$$

6. Meaning of the negative sign

The negative sign ensures **correct direction of heat flow**:

- If temperature decreases in the positive x-direction:

$$\frac{dT}{dx} < 0$$

- Then:

$$q > 0$$

This means heat flows in the **positive x-direction**, from hot to cold.

Figure 21: Virtual tutor going over differentiation and highlighting sign details

Conclusion

This study demonstrates that the intentional integration of artificial intelligence within a flipped thermodynamics course can enhance student engagement, conceptual understanding, and instructional efficiency. By leveraging AI to support pre-class preparation, automate low-value procedural tasks, and redesign in-class problem-solving activities, instructional time was more effectively devoted to conceptual reasoning, interpretation of results, and engineering judgment. These outcomes align with the core goals of flipped pedagogy and address persistent challenges in teaching foundational thermodynamics concepts.

The findings also underscore that AI is most effective when used as pedagogical support rather than a substitute for instruction. Instructor oversight, careful prompt design, and alignment with learning objectives remain essential to ensuring accuracy, rigor, and meaningful learning. Additionally, the use of freely accessible AI tools supports equitable access while offering scalable, personalized learning support. Although results are preliminary, they suggest that AI-enabled flipped instruction holds significant promise for improving both teaching practice and student learning in engineering education. Future work will focus on expanded assessment, longitudinal analysis, and refinement of implementation strategies to further evaluate learning outcomes and best practices.

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