GPThermo: An In-House Generative Artificial Intelligence Tutor for Thermodynamics

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Abstract

Generative artificial intelligence (GenAI) has become ubiquitous. Convincing language complemented by constant modifications and upgrades have made GenAI models, such as OpenAI's ChatGPT, an appealing tool to address complex problems. According to a survey by Intelligent.com nearly a third of college students in AY 2022-2023 used ChatGPT for schoolwork and 77.4% of them were likely to recommend using it to study to another student. Despite their appeal, these models have proven flawed in answering technical prompts. Their convincing language may entice the user to trust the responses without verifying them. For example, the authors failed to retrieve accurate thermodynamics properties of some common substances from three publicly available models (OpenAI's ChatGPT, Anthropic's Claude, and Google's Gemini). Notwithstanding the inaccuracy of the responses, the conversation suggested some promising capabilities. For instance, with instructive prompts by the user, the models were able to reduce their error percentages significantly.

Thermodynamics is one of the early core courses that students in Mechanical Engineering, Chemical Engineering, and Aerospace Engineering, among others take. This study aims to develop a GPT-based model focused on thermodynamics using publicly available resources, such as substance properties. Once proven successful, the model can be adopted by other institutions and adapted to similar courses.

Keywords

Artificial Intelligence, Thermodynamics, AI

1 Introduction

Thermodynamics is one of the most challenging subjects for engineering students and professionals alike. It often serves as a so-called gateway course (John M Pfotenhauer, 2015; Koch, 2017). Gateway courses are among the contributors resulting in students leaving STEM, even among high-performers (Koch, 2017). Thermodynamics requires high cognitive load—a primary factor that pushes students out—due to its heavy reliance on complex concepts, data-intensive calculations, and the application of intricate physical laws (Orlando M Ayala, 2017). As such, it is often regarded by students as difficult and abstract (Patrick Tebbe, 2007) and consistently rank among the most challenging in engineering programs (Derek Baker, 2000; V Ismet Ugursal, 2015). Beyond its complex concepts, thermodynamics presents a practical challenge: it demands constant lookups of property values from massive data tables. Students and engineers must flip through

Pressure Conversions: 1 bar = 0.1 MPa		Specific Volume m³/kg		Internal Energy kJ/kg		Enthalpy kJ/kg			Entropy kJ/kg · K		
= 10 ² kPa		Sat.	Sat.	Sat.	Sat.	Sat.	1000	Sat.	Sat.	Sat.	24.7
emp.	Press.	Liquid	Vapor	Liquid	Vapor	Liquid	Evap.	Vapor	Liquid	Vapor	Temp
°C	bar	$v_f \times 10^3$	$v_{\rm g}$	u _f	ug	hţ	h _{fg}	hg	Sį	S _g	°C
-60	0.3749	0.6833	0.5370	-21.57	203.67	-21.55	245.35	223.81	-0.0964	1.0547	-60
-50	0.6451	0.6966	0.3239	-10.89	207.70	-10.85	239.44	228.60	-0.0474	1.0256	-50
-45	0.8290	0.7037	0.2564	-5.50	209.70	-5.44	236.39	230.95	-0.0235	1.0126	-45
-40	1.0522	0.7109	0.2052	-0.07	211.68	0.00	233.27	233.27	0.0000	1.0005	-40
-36	1.2627	0.7169	0.1730	4.29	213.25	4.38	230.71	235.09	0.0186	0.9914	-36
-32	1.5049	0.7231	0.1468	8.68	214.80	8.79	228.10	236.89	0.0369	0.9828	-32
-30	1.6389	0.7262	0.1355	10.88	215.58	11.00	226.77	237.78	0.0460	0.9787	-30
-28	1.7819	0.7294	0.1252	13.09	216.34	13.22	225.43	238.66	0.0551	0.9746	-28
-26	1.9345	0.7327	0.1159	15.31	217.11	15.45	224.08	239.53	0.0641	0.9707	-26
-22	2.2698	0.7393	0.0997	19.76	218.62	19.92	221.32	241.24	0.0819	0.9631	-22
-20	2.4534	0.7427	0.0926	21.99	219.37	22.17	219.91	242.09	0.0908	0.9595	-20
-18	2.6482	0.7462	0.0861	24.23	220.11	24.43	218.49	242.92	0.0996	0.9559	-18
-16	2.8547	0.7497	0.0802	26.48	220.85	26.69	217.05	243.74	0.1084	0.9525	-16
-14	3.0733	0.7533	0.0748	28.73	221.58	28.97	215.59	244.56	0.1171	0.9490	-14
-12	3.3044	0.7569	0.0698	31.00	222.30	31.25	214.11	245.36	0.1258	0.9457	-12
-10	3.5485	0.7606	0.0652	33.27	223.02	33.54	212.62	246.15	0.1345	0.9424	-10
-8	3,8062	0.7644	0.0610	35.54	223.73	35.83	211.10	246.93	0.1431	0.9392	-8
-6	4.0777	0.7683	0.0571	37.83	224.43	38.14	209.56	247.70	0.1517	0.9361	-6
-4	4.3638	0.7722	0.0535	40.12	225.13	40.46	208.00	248.45	0.1602	0.9330	_4
-2	4.6647	0.7762	0.0501	42.42	225.82	42.78	206.41	249.20	0.1688	0.9300	-2
0	4.9811	0.7803	0.0470	44.73	226.50	45.12	204.81	249.92	0.1773	0.9271	0
2	5.3133	0.7844	0.0442	47.04	227.17	47.46	203.18	250.64	0.1857	0.9241	2
4	5.6619	0.7887	0.0415	49.37	227.83	49.82	201.52	251.34	0.1037	0.9213	4
6	6.0275	0.7930	0.0391	51.71	228.48	52.18	199.84	252.03	0.2025	0.9184	6
8	6.4105	0.7974	0.0368	54.05	229.13	54.56	198.14	252.70	0.2109	0.9157	8
10	6.8113	0.8020	0.0346	56.40	229.76	56.95	196.40	253.35	0.2193	0.9129	10
12	7.2307	0.8066	0.0326	58.77	230.38	59.35	194,64	253.99	0.2276	0.9102	12
16	8.1268	0.8162	0.0320	63.53	231.59	64.19	191.02	255.21	0.2442	0.9102	16
20	9.1030	0.8162	0.0251	68.33	232.76	69.09	187.28	256.37	0.2442	0.8996	20
24	10.164	0.8369	0.0239	73.19	233.87	74.04	183.40	257.44	0.2007	0.8944	24
28	11.313	0.8480	0.0232	78.09	234.92	79.05	179.37	258.43	0.2936	0.8893	28
-		71077000	777						-	1000000	
32 36	12.556 13.897	0.8599	0.0186	83.06 88.08	235.91 236.83	84.14 89.29	175.18 170.82	259.32 260.11	0.3101	0.8842	32 36
											10.77
40	15.341	0.8858	0.0151	93.18	237.66	94.53 101.21	166.25	260.79	0.3429	0.8738	40 45
45	17.298	0.9039	0.0132	99.65	238.59		160.24	261.46	0.3635	0.8672	
50	19.433	0.9238	0.0116	106.26	239.34	108.06	153.84	261.90	0.3842	0.8603	50
60	24.281	0.9705	0.0089	120.00	240.24	122.35	139.61	261.96	0.4264	0.8455	60

Figure 1-A typical tabulated properties of a common substance in thermodynamics. The table is extracted from (Michael J Moran, 2010).

these tables, find the right values, and then use them in detailed calculations. Even simple problems can turn into lengthy processes as each new step requires another round of table lookups and number crunching.

While there exist some commercial software such as EES (F-Chart Software, 2024), REFPROP (NIST, 2024), CoolProp (Ian H. Bell, 2014), Interactive Thermodynamics: IT (Shapiro, 2023) and free calculators (IRC, 2023), the thermodynamic properties of substances are still mostly extracted from extensive tables often found as appendices at the back of the reference textbooks. A typical thermodynamics table is shown in Figure 1. With more students opting out of owning textbooks and not having access to the commercial software packages, the properties of substances, which are the building blocks of any thermodynamics analysis, remain inaccessible to many students. This challenge is exacerbated once the student is no longer enrolled in the course.

Another challenge that many students in engineering fields, including thermodynamics, face is the unnecessarily complex calculations. The authors believe in equipping the future engineers with tools to comprehend and analyze complex mathematical problems. However, we find the tedious and repeated calculations that involve mathematical operations on data with a wide range of order of magnitude and fine resolutions redundant. Complex calculations can be overwhelming and impede understanding of underlying concepts. Alternatively, simplifying calculations through software tools or alternative methods can free up cognitive resources, allowing students to focus on grasping the key principles. When calculations are simplified, students can see the connection between theory and application more clearly, leading to deeper understanding and improved retention of knowledge. By focusing on problem-solving strategies and interpreting results rather than intricate calculations, students can develop valuable critical thinking and analytical skills.

In the current era, students frequently turn to AI technologies to assist them in understanding difficult subjects (Juan Dempere, 2023; Libert, 2023). A recent survey discovered over 89% of college students have used ChatGPT to help with a homework assignment (Libert, 2023). The current publicly available AI models (e.g., ChatGPT, Copilot, Claude, Gemini), however, are not designed specifically for engineering and thermodynamics problems. Consequently, they often produce inaccurate or incomplete responses when applied to the specialized nature of these courses. The inaccuracy of the results, coupled with convincing language of large language models (Carrasco-Farre, 2024), pose a significant risk as students may unknowingly rely on incorrect information. A sample conversation between the authors and ChatGPT is documented in Appendix A. In this conversation, ChatGPT failed to provide a clear and accurate response to the prompt: "What is the temperature of water at an enthalpy of 906 kj/kg and pressure of 894 mpa?" The input properties (enthalpy and pressure) are deliberately chosen outside the range of normally published tables in textbooks (Michael J Moran, 2010), and units are incorrectly typed to mimic typical student submissions.

While general-purpose AI models are becoming more available, technical communities may still benefit from developing their own specialized AI models to incorporate their unique domain expertise, terminology, methodologies, and standards. This study addresses this gap by developing a robust AI model designed specifically for thermodynamics. The AI model, **GPThermo**, is equipped to handle vast data tables, perform precise calculations, and provide detailed and accurate feedback on complex thermodynamics problems.

2 Model Design and Development

Training a large language model (LLM) requires a significant amount of computing power. To save resources, a common strategy is to start with a pre-trained foundation model and then enhance it to fit the needs of a specific application (Aaron Parisi, 2022). In the case of **GPThermo**, the key improvement over publicly available models like ChatGPT is its ability to work with private data and interact directly with code to determine substance properties and perform thermodynamics calculations. It builds on the GPT-40 foundation model by adding two features: tool augmentation and retrieval augmentation (Aaron Parisi, 2022).

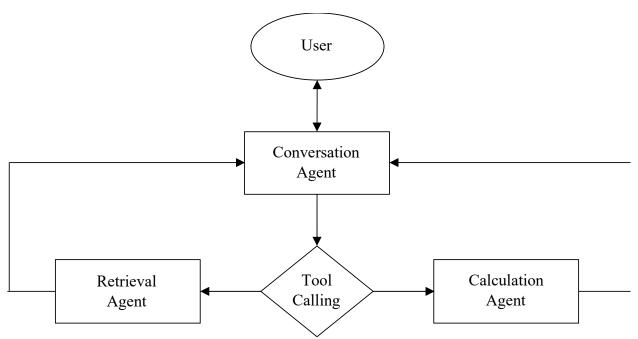


Figure 2 - Multi-agent Architecture of GPThermo.

- 1. Tool augmentation enables the model to run custom code, such as calling a function to determine substance properties or a calculator function to compute thermodynamic properties.
- 2. Retrieval augmentation allows the model to access and use private or specialized data not included in its original training; such as proprietary property tables or specific fluid identifiers.

These augmentations allow **GPThermo** to offer domain-specific functionality without needing to retrain or scale up the foundation model itself. The architecture of the model is illustrated in Figure 2 and described below:

1. Main Conversation Agent:

The core of the system is a conversation agent built on GPT-40, which is configured with detailed instructions. These instructions define the roles of various secondary agents and specify the conditions under which each should be activated. Upon receiving any user input, the conversation agent determines whether a secondary agent needs to be engaged. This decision is made through an *if-else* logic structure that routes the input to the appropriate secondary agent. In certain cases (e.g., complex calculations), a secondary agent may delegate specific tasks to even more specialized sub-agents (not shown in the diagram).

2. Secondary AI Agents:

There are two secondary agents, each with its own focused role and instruction set. This modular setup minimizes the computational load by keeping each agent lightweight and task-specific:

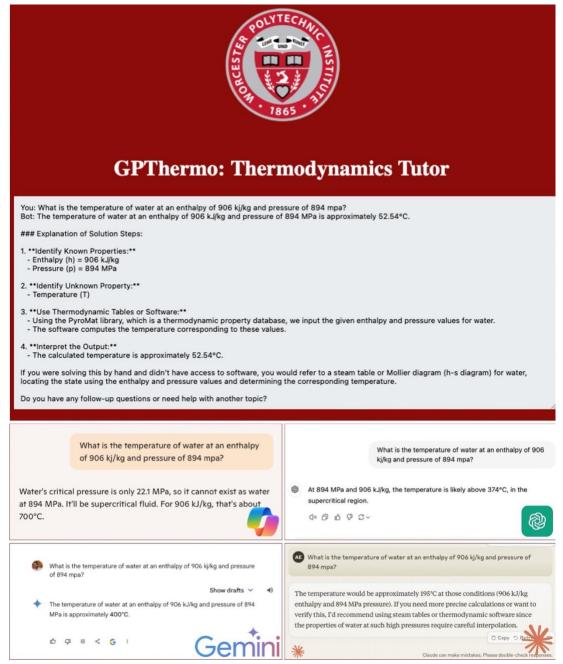


Figure 3 - GPThermo's response (top center) to the sample thermodynamics prompt (What is the temperature of water at an enthalpy of 906 kj/kg and pressure of 894 mpa?) versus the leading public AI models.

- Retrieval Agent:
 Responsible for extracting information from supervised sources such as proprietary property tables or specific fluid identifiers.
- Calculation Agent: Executes mathematical operations using Python-based code to provide quantitative outputs.

	GPThermo	GPT-40	Gemini	Claude	Copilot
Q1	1	0	0	0	0
Q2	1	0	0	0	0
Q3	1	1	1	1	1
Q4	1	0	0	0	0
Q5	1	0	0	0	1
Q6	1	0	0	0	0
Q7	1	0	0	0	0
Q8	1	0	0	0	0
Q9	1	0	0	0	0
Q10	1	0	0	0	0
Q11	1	0	0	0	0
Q12	1	0	0	0	0
Q13	0	0	0	0	0
Q14	1	0	0	0	0
Q15	1	0	0	0	0
Q16	1	0	0	0	0
Q17	1	0	0	0	1
Q18	1	0	0	0	0
Q19	1	1	1	1	1
Q20	1	1	1	1	1
Score	95%	15%	15%	15%	25%

Figure 4 - The responses of GPThermo and leading models excel on the validation questions. Correct answers are marked with a 1, highlighted in green, while incorrect answers are marked with a 0, highlighted in red.

3. Output Loop and Response Generation:

Each secondary agent returns its output to the main conversation agent. This process may iterate several times within a single user query to compile a complete and accurate response. Once all necessary information is gathered and processed, the conversation agent delivers a final, synthesized reply to the user.

3 Validation and Results

A benchmark test was required to validate the new model's ability to interpret and correctly respond to thermodynamics questions. Twenty questions relating to fluid state and thermodynamic processes were tested against **GPThermo**. These questions were also tested against four leading publicly available models: OpenAI's ChatGPT, Google's Gemini, Anthropic's Claude, and Microsoft's Copilot. The questions were selected to have clear numerical answers, enabling a more precise quantitative comparison of the models. The performance of each model was then evaluated by measuring the accuracy of its results, considering answers correct if they fell within 1% of the analytical solution. The performance of **GPThermo** compared to the publicly available models is

exemplified in Figure 3. The complete comparison of the performance of the models is shown in Figure 4. Overall, GPThermo responded accurately to 95% of the questions, as compared to the 15%-25% by the four other publicly available models. The performance scores have remained relatively consistent as the authors have improved GPThermo in response to the continuous evolution of public models. The full list of questions is provided in Appendix B.

4 Boarder Impacts and Conclusions

The proposed project has the potential to significantly advance discipline-based educational research, particularly in engineering fields that rely heavily on thermodynamics concepts, such as Mechanical, Aerospace, and Chemical Engineering. By developing **GPThermo**, a generative AI model tailored to specific engineering domains, this work contributes to the expanding field of AI-assisted learning and the creation of intelligent educational tools.

A key innovation of this project lies in the development of a subject-specific AI model alongside a companion validation tool, moving beyond general-purpose educational AI. It contributes to the fields of engineering education, AI in education, and educational technology by (1) demonstrating the feasibility of customizing large language models for STEM education, and (2) providing a framework for validating such tools rigorously.

In particular, GPThermo offers promising benefits for underrepresented and resource-limited students. By providing instant, accurate, and domain-specific feedback, the model has the potential to fill instructional gaps often found in under-resourced learning environments. It promotes greater equity and accessibility by supporting self-guided learning and reducing dependency on instructor availability. Additionally, the lightweight, modular design of the system could make deployment easier for institutions with limited computational infrastructure.

While the study notes the potential for GPThermo to be adopted at other institutions, the tool's successful adoption will depend on factors such as curriculum alignment, faculty acceptance, and institutional support. Integrating AI into existing courses poses challenges, including the risk of resistance to automation and the need to train faculty on the tool's pedagogical uses and limitations. Additionally, providing students with access too early in their learning process may lead to overreliance on the model, potentially preventing them from developing foundational skills such as determining thermodynamic properties or performing calculations independently.

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Appendix A

A sample conversation between the authors and ChatGPT (GPT-40)

User: What is the temperature of water at an enthalpy of 906 kj/kg and pressure of 894 mpa?

Assistant: To determine the temperature of water at a specific enthalpy (h) and pressure (P), we can use water's thermodynamic properties based on steam tables or the International Association for the Properties of Water and Steam (IAPWS) correlations.

1. Given Data:

- Enthalpy (h): 906 kJ/kg
- Pressure (P): 894 MPa
- 2. Observation: The pressure 894 MPa is extremely high and not within typical ranges of liquid water or saturated steam under standard conditions. At this pressure, water likely exists in a compressed (subcooled) liquid state or a supercritical state, depending on the temperature.

3. Procedure:

- Use thermodynamic property tables for water (e.g., IAPWS-IF97) to find the temperature corresponding to this enthalpy and pressure.
- At extremely high pressures like 894 MPa, the data would likely fall in the supercritical region. Here, specific temperature-enthalpy relationships govern the properties.

4. Calculation Tool:

The exact answer would require specialized software or reference to detailed thermodynamic data tables.

User: Yes.

Assistant: To calculate the temperature for water at h = 906 kJ/kg and P = 894 MPa, I'll use an approximation based on thermodynamic principles for supercritical water.

Here's how we'll proceed:

1. Supercritical Region: Since P = 894 MPa, this is far beyond the critical pressure of water ($P_{\text{crit}} = 22.064$ MPa). At this pressure, the relationship between enthalpy and temperature requires detailed thermodynamic tables or equations of state.

2. Estimation Tools: I'll use a thermodynamic calculation to narrow down the temperature range.

[Error in calculating...]

Assistant: I could not use the IAPWS (International Association for the Properties of Water and Steam) library to perform the calculation in this environment. However, I can guide you on how to calculate it or approximate the value using other tools.

Options for Determining the Temperature

- 1. Online Tools or Software:
 - Use a property calculator like Engineering Toolbox or CoolProp.
 - Tools like REFPROP or EES can also provide detailed thermodynamic property calculations.
- 2. Approach with Thermodynamic Tables:
- Refer to supercritical water property tables for P = 894 MPa. The enthalpy h = 906 kJ/kg will correspond to a unique temperature.

Would you like me to look up this value for you online or guide you to an appropriate tool?

User: Yes.

Assistant: Given the extremely high pressure of 894 MPa (which is 8,940 times atmospheric pressure) and an enthalpy of 906 kJ/kg, water is in a supercritical state. In this state, the distinction between liquid and vapor phases disappears, and water exhibits unique properties.

Determining the exact temperature corresponding to these conditions requires precise thermodynamic data. However, based on typical supercritical water behavior, an enthalpy of 906 kJ/kg at such a high pressure suggests a temperature in the approximate range of 350°C to 450°C.

For precise calculations, you can use specialized tools and resources:

- NIST Chemistry WebBook: Provides thermophysical properties of fluid systems, including water.
- Steam Tables Online: Offers calculators based on IAPWS formulations for water and steam properties.
- Thermophysical Properties Calculator: An online tool for calculating properties of water and steam.

These resources can help you obtain accurate thermodynamic properties for water under various conditions.

Appendix B

The list of questions designed for the initial validation of the model. Note the questions intentionally include mistyped units and grammatical errors to mimic typical student submissions.

- 1. What is the temperature of water at an enthalpy of 906 kj/kg and pressure of 894 mpa?
- 2. Refrigerant r-134a enters a throttling valve at a temperature of 58C and pressure of .2 mpa. Assuming the process is adiabatic and no work is done, what will be the pressure if the refrigerant exits at 55C?
- 3. A water heater uses a heating element with a resistance of 750 ohms to raise the temperature of 1 kg of water from 60 to 96 degrees celcius. What is the minimum amperage required to achieve this in 30 seconds, assuming the process happens in an open container under atmospheric pressure?"
- 4. what is the entropy of water at 310 K and 2 bar?
- 5. A piston of area 4m² pushed against 400c steam with a specific volume of 990 m³/kg. How much force is needed to hold the piston still?
- 6. What will the change in internal energy of steam be if it is heated from 100c and 2 mpa to 300c at a constant pressure?
- 7. Natural gas enters a pipe at 300K. It is cooled to 200K at a constant pressure of 2 bar. What will the change in internal energy be due to this process?
- 8. A piston-cylinder assembly containing 2kg of r-134a at 10c and .06mpa undergoes a cooling process to -20c. What is the total internal energy, in kj, of the fluid in the cooled state?
- 9. An isothermal compression process instantly vaporizes 150c water at a quality of .3 to 1. What is the gain in entropy from this process?
- 10. Steam is delivered to a paper plant at 550K and 4mpa. If the steam is delivered with a mass flow rate of 600kg/s, what is the power provided to plant?
- 11. Steam enters a turbine at 545c and 6mpa. It exits as a saturated vapor at 2mpa. What is the work done by the turbine?
- 12. Saturated steam enters a condenser at 2 mpa. How much work is required to pump the water leaving the condenser at 6mpa?
- 13. The instructions on an MRE require it is boiled at for 8 minutes at 1 atm to sufficiently cook the food. How long, in minutes, will it need to boil to transfer the equivalent energy if cooked on a mountain where the atmospheric pressure is only .8 atm?
- 14. Steam undergoes isenthalpic expansion where the initial state was 9bar and 888C. After the process, the steam is at a pressure of 2bar. What is the temperature drop?

- 15. What is the enthalpy of steam held at 500c and 5.64 mpa?
- 16. Saturated steam enters a pipeline at a mass flow rate of 400 kg/sec. If the temperature of the steam is 200c and the radius of the pipe is .5 meters, determine the velocity of flow.
- 17. What is the specific volume of saturated water when it has temperature of 30c?
- 18. What will be the specific entropy of steam that is half vapor and half liquid at 58c?
- 19. Which has a greater internal energy, steam at 400c and 2mpa, or steam at 500c and 1.5 mpa?
- 20. A rigid tank contains 2 kmol of N2 and 6 kmol of CO2 at 300 K and 15 MPA. Estimate the volume of the tank using the ideal gas law.