A Project-based Learning Activity Involving Hybrid Intelligence in the Undergraduate Engineering Class

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Abstract Artificial intelligence (AI) is increasingly embedded in academic practice, creating opportunities to support learning and improve educational outcomes. We implemented a project-based learning activity in an undergraduate engineering course in which students used meteorological data to construct a temperature time series and assess local climate change at a selected location from the national weather station network. They transformed raw datasets, organized files in spreadsheets, and automated routine calculations by prompting a large language model (LLM) to generate executable code for a collaborative programming platform. As a structured form of human–AI collaboration, the activity contributes to discussions of hybrid intelligence in education by allowing students to focus on higher-level cognitive tasks.

Keywords Prompt design · Collaborative programming · Data analysis · Climate change · Large Language Model

1 Introduction

The ubiquity of artificial intelligence (AI) is resetting many work routines in a variety of sectors. However, the acceptance of its beneficial aspects is clouded by the fear of replacing human labor. As often occurs with disruptive technologies, we are still adjusting behavior, and to navigate in this environment as AI users, the evidence suggests that we should focus on its beneficial aspects. This will help us better understand how human abilities will likely adapt in the near future.

In education, more specifically higher education in colleges and universities, we face at least 3 major perspectives *on the use* of AI systems: students, faculty members, and administrative staff [1, 2]. Three categories of *application of* artificial intelligence

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in learning and education (AIED) are: student-focused, teacher-focused, and system-focused [2]. In addition, it is based on how large language models (LLMs) are built, and the paradigms are data-driven and knowledge-based platforms [2]. Data-driven AI is widely used across various domains of application, while knowledge-based AI relates to a more specialized type of system, particularly useful in educational settings. For context, the *Generative Pre-Trained Transformer* (GPT) series of models developed by *OpenAI* belongs to the data-driven category. The six (6) main applications of LLMs in education are: chatbots, learning content generation, automated assessment and feedback, task support tools, learning support tools, and intelligent tutoring systems [3]. Intelligent Tutoring Systems (ITS), due to their potential for personalization, have already been used prior to the recent boom in AI popularity.

Regarding applications involving task support tools, an ITS was proposed to teach the Python programming language using ChatGPT [4]. They found that the system supports the learning of Python for novice programmers in computer science, but they also found that there was an overreliance on the system that may limit the ability of these students to develop problem-solving skills. In an investigation with postgraduate mathematics students, [5] reported on the use of ChatGPT to facilitate the learning of *GeoGebra*, a popular mathematical educational software. The value of adding prompt interaction with ChatGPT to personalize *Geogebra* teaching for different learning styles was recognized by the authors. These studies promoted the use of generative AI (genAI) to enhance computational skills learning, a natural application of LLMs. In such cases, the AI model serves as an assistant to students, as portrayed in the emerging field known as *Agentic Workflow for Education* (AWE) [6]. A less explored use of genAI is in augmenting human learning by symbiotically interacting with the AI agent, with the human specialists (the teachers) and with other systems (ITS for example). This is called hybrid intelligence, and – as found in [7] – prompting the chatbot with queries that go beyond simply requesting an immediate answer is key in developing higher cognitive abilities.

The hybrid intelligence use of AI with subjects that are not directly associated with computer and mathematical learning has not been explored extensively yet, and here an example is given as a contribution to this area. By synergistically using prompt strategies, spreadsheets, and collaborative programming, we show one way of applying genAI as a *task support tool* in a climatology course for undergraduate environmental and sanitary engineering students in a project-based learning activity. The assignment evolved from simply exploring published research in its first offer to building a one-year time series of temperature and rainfall anomalies for a given location using spreadsheets only (no AI directives for the students) and finally to the present version where spreadsheets are used with the help of AI and collaborative programming to produce a five-year time series temperature anomaly chart for a given location. Students also need to reach a conclusion about the time series' linear trend being indicative of warming, cooling, or neither warming nor cooling. If a warming trend is detected, they are further encouraged to explore the possibility of an *urban heat island* if the results apply to a well developed built area.

The article is organized as follows: the tools and techniques (spreadsheets, prompt design, and collaborative programming) are described in section 2. The results of applying these methods to the project-based learning activity are given in section 3. In section 4, some approaches by other authors are briefly mentioned and a summary is presented. Concerns and opportunities about the widespread use of artificial intelligence (AI) in this new reality are highlighted.

2 Data cleaning and transformation

The use of spreadsheets, prompt design, and collaborative programming make the set of techniques used in the project-based learning activity. Together, they take two types of raw weather data files downloaded from the National Meteorological Institute (INMET) to produce a time series of temperature standardized anomalies with the accompanying linear trend line. Gemini is the LLM chosen since the university offers the paid version of the Google Workspace for Education suite, allowing faculty and students to have higher usage limits with Google's flagship LLM. The full workflow was also done with a spreadsheet (Excel) to have a reference to validate the results obtained with AI.

2.1 The use of spreadsheets

There are at least three spreadsheet options: Microsoft Excel, LibreOffice Calc and Google Sheets. In principle, any one of these can be used, but Excel and Calc have a richer set of functions when compared to Google Sheets. Both Excel and Calc include interchangeable file types and Google Sheets also has the option to save in Excel's and Calc's file formats (xlsx and ods).

The project requires the download of 30 years of manual weather data (three values per day, 0, 12 and 18 UTC) going from 1991 to 2020, and 5 years of automatic hourly weather data (24 values per day) going from 2021 to 2025. Due to INMET's internet traffic policy, only 6 months can be downloaded at a time. This amounts to storing 60 files from the manual station and 10 files from the automatic one. These files come in csv (comma-separated value) format but their names are not unique. A first step is to rename them following a given rule. The 60 files for the 30-year averages are named as "`cyyyy-n.csv`", where"`c`" stands for "conventional", "`yyyy`" is the year, and "`n`" is either "`1`" or "`2`". The 10 files from the automatic station were named as "`ayyyy-n.csv`", where the "`a`" stands for "automatic", and the other letters having the same meaning as before. For example, a file named "`c1994-2.csv`" tells that it comes from the conventional (manual) station for the second semester (july to december) of the year 1994. The 30-year average spanning from 1991 to 2020 is known as the climatological normal [8]. Data from the automatic station ideally should go from 2021 to 2025, but the possibility of missing values in a given raw file may require downloading data from 2020 or earlier to have at least the 5 most recent years of the record.

2.1.1 Handling manual weather station data

After downloading the 60 files and assigning their names in accordance with the rule previously described, Excel was used to merge them into 30 annual files. The data is organized in twelve fields (columns) including date, time, temperature at 0, 12 and 18 UTC, daily maximum/minimum temperatures, and seven other weather elements that are removed during the cleanup process. Due to having three times for the elements in the conventional dataset, there are three rows per day. Furthermore, leap years need to be taken into account, and the 0 UTC temperature of 01/Jan/2021 is also needed to have the mean value for 31/Dec/2020 [1].

2.1.2 Handling automatic weather station data

A similar transformation is performed with the raw files from the automatic station to have 5 csv files, one for each year from 2021 to 2025 if no significant missing data are detected. Since weather elements from the automatic station are registered for each hour of the day, a daily mean temperature results by averaging these 24 hourly temperatures in Excel. This daily mean temperature is stored in one of the 24 rows for a given day, and the other 23 are removed to leave the data file with 365 rows (366 on leap years) before attaching the files in the Gemini chat.

2.2 Prompt design

The diversity of new LLMs currently under development raises a flag on how to interact with them effectively. Different models are built for distinct purposes (for example, fast answers, deep thinking, complex tasks, etc.), and the choice can affect how prompts are structured to achieve a desired outcome. The emphasis on *context* becomes important in the planning of prompt strategies. Whether one wishes to analyze data, create content, or generate computer code, having a clear context is useful to reduce the risk of hallucination by LLMs [9]. The design of structured prompts is a digital competence [10], and a higher level of cognition is a desirable trait to formulate them. It has been found that undergraduate engineering students lack the habit of using LLMs in a more structured way, a literacy domain related to creating with AI [11].

Some of the most popular prompt techniques with their main characteristics are presented in table 1. In this project-based learning activity, a *Chain-of-Thought* (CoT) approach is used. Three structured prompts are created with some of the most common elements of prompt-formulating techniques. They establish the *persona* (character) and *context* initially, followed by *tasks* and *evaluations* in the main prompt structure. The first prompt serves to check the consistency of the daily mean weighted temperatures (TMCs) for just one year after following the data cleaning steps described in section 2.1.1. This is accomplished by instructing the LLM with *"show a preview of this transformation*

[1] 0 UTC of 01/Jan is 9 PM of 31/Dec since Brazil is mostly at UTC-3.

here in the chat", assuring that Gemini's replies can be directly compared with the spreadsheet calculations before asking to create code. After this validation, the second prompt is given, explicitly asking Gemini to return the Python script that will be run on Google Colab (section 2.3). The script is then executed for each year to produce the required csv files with the information needed for the 30-year climatological normal.

Table 1 Comparison of three prompting techniques

Prompting technique	Key characteristic
Zero-shot	prompt for a task without prior training
Few-shot	give a few examples to provide context
Chain-of-thought (CoT)	prompts with step-by-step reasoning

Finally, the third prompt is formulated for the automatic station data with the instructions described in section 2.1.2. The practice gained with the automation of steps for the manual station data allows the formulation of this prompt to produce a single csv file with the 5 years of daily mean temperatures directly and ready to be merged with the single 30-year climatological normal information. The *"show a preview of this transformation here in the chat"* directive is also given to Gemini, and if inconsistencies are found, a new iteration is made until the LLM output matches the result of the spreadsheet calculations.

2.3 Data analysis

The third step before plotting the time series in Excel is to run the Python codes created with Gemini. To do so, the scripts are executed in the Colab notebook environment, and the 35 resulting csv files (30 for $TMCs$, and 5 for the daily mean values of the automatic station) are merged into a single file. The 1991-2020 climatological normal is the average of all $TMCs$ for each day in the 30-year time span. The relative temperature anomaly is obtained with:

$$\frac{T - \bar{T}}{\sigma} \tag{1}$$

where T is the daily mean temperature of the automatic weather station data from 2021 to 2025, $\bar{T}$ is the climatological normal of 1991-2020 for each of the 365 days of the year and σ is the standard deviation of $\bar{T}$. Relative anomalies can then be classified as weak or strong on the basis of threshold criteria. They can also be counted to check if there are more positive than negative anomalies, which already gives an indication of the trend (anomaly *duration* is also important to verify persistence).

Next, a linear regression is applied to these anomalies to verify the trend in the data [12]. The slope is given by:

$$\text{Slope} = \frac{n \sum_{n}^{i=1} A_i \cdot B_i - \sum_{n}^{i=1} A_i \cdot \sum_{n}^{i=1} B_i}{n \sum_{n}^{i=1} A_i^2 - \left(\sum_{n}^{i=1} A_i\right)^2} \tag{2}$$

where n is the number of data points, A_i is the temperature rank sorted by increasing time (independent variable) and B_i the corresponding relative temperature anomaly (dependent variable).

The Spearman correlation is another metric that is frequently used in climate trend studies [12]. It is a single number that can take any value between ±1, where a positive or negative number indicates a trend of warming or cooling, respectively. A value near zero indicates a weak correlation. It is given by:

$$\rho = 1 - \frac{6 \cdot \sum_{i=1}^{n} (A_i - B_i)^2}{n \cdot \left(n^2 - 1\right)} \tag{3}$$

where ρ is the Spearman correlation, A_i is the temperature rank sorted with increasing time (original rank), B_i is the temperature anomaly's rank sorted in *increasing order of temperature anomalies* and n the number of data points. Note that B_i in eq. (3) is not the same quantity as B_i in eq. (2).

2.4 Summary of the approach

The techniques and tools necessary for this project-based climatology learning activity have been described above. Keeping in mind that it is an activity for undergraduate engineering students, the instructor guides them in at least 4 in-class sessions, and they are expected to finish the analysis and reach a conclusion about the local climate. Thus, directions are given to have all raw data files from the National Institute of Meteorology available. Another session is needed to have students name the files accordingly and perform the initial data cleaning using Excel. In this session, the first and second prompts are sent to Gemini to transform the data and obtain the first Colab notebook for the TMC computations. A third session is held to process the data from the automatic station, and a final one to obtain the trend metrics based on a spreadsheet template prepared by the instructor. An overview of all steps in sequence and the tools used for each one is given in figure 1.

3 Results

The prompts used to transform the raw INMET files are presented next. While they follow a structured approach, the text is not rigid (variations are possible). We begin by assigning a *persona* and establishing the *context*. These two directives are given, and then Gemini responds. After that, the step-by-step sequence is provided in one single prompt for *tasks* and *evaluations*.

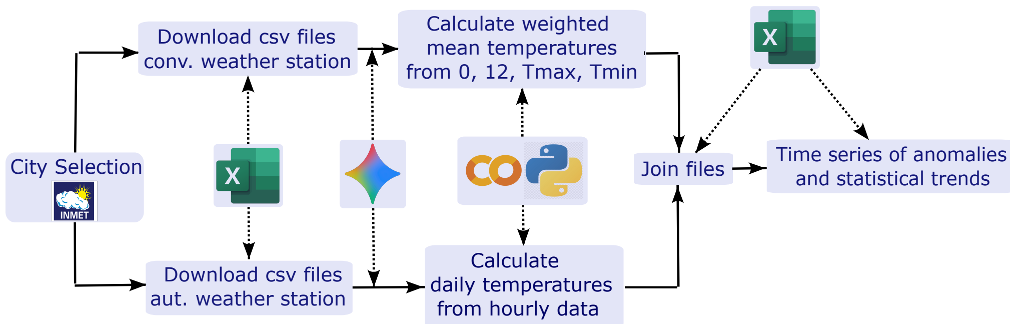

Fig. 1 Schematic flow of project steps and tools used.

3.1 Prompts to tranform csv files from the manual station

The first prompt transforms two files for a single year. This is to verify the validity of the prompt by comparing its result with the equivalent transformation done by using Excel directly.

PERSONA and CONTEXT:

You are a research assistant who will help me transform *csv* files. There is no need to offer suggestions after each prompt. Just execute what is being asked from you in each prompt.

TASKS and EVALUATION:

1. The two `csv` files attached to this chat contain the following column fields: Data; Hora (UTC); Temp. [Hora] (C); Umi. (%); Pressao (hPa); Vel. Vento (m/s); Dir. Vento (m/s); Nebulosidade (Decimos); Insolacao (h); Temp. Max [Diaria] (h); Temp. Min. [Diaria]; Chuva [Diaria] (mm). Combine these 2 files in one `csv` file for 1991. Do not change the format of the `csv` files, keep ";" as a field delimiter, and "," as the decimal point. Keep the original format of the dates with "dd/mm/aaaa" as well.

2. Remove all data except for the first three fields, that is, Data; Hora (UTC); Temp. [Hora] (C), the third to last and the penultimate, that is, Temp. Max. [Diaria] (h); Temp. Min. [Diaria] (h). The transformation should keep only the values for these five fields with their respective headings. Show a preview of this transformation here in the chat.

3. Subtract 300 from the rows in the field Hora (UTC) with values 1200 and 1800. Add 2100 to the rows with the field Hora (UTC) is equal to 0000 and change the date to the day before in all rows where 2100 was added to the field Hora (UTC). For example, if the row has 01/01/1991; 1200; etc, change to 01/01/1991; 900; etc. If the row has 01/01/1991; 0000; etc., change to 31/12/1990; 2100; etc. Rename the heading from (UTC) to (UTC-3). Show a preview of the transformation here in the chat.

4. Delete the first row with the date 31/12/1990. Show a preview of this transformation here in the chat.

5. Calculate the weighted mean temperature with the following equation for EACH DAY: add Tmax with Tmin with T9 and with two times T21, and then divide this sum by five. Store the result in a new column named TMC (C) in the same row with the field Hora (UTC-3) from 2100. Show a preview of this transformation here in the chat.

6. Delete the rows with the field Hora (UTC-3) for 900 and 1500. Show a preview of this transformation here in the chat.

7. Delete the columns with the fields Hora (UTC-3), Temp. [Hora] (C), Temp. Max. [Diaria] (h) Temp. Min [Diaria] (h). The resulting transformation should contain only the columns Data and TMC (C) with one single value for TMC for each day of the year. Show a preview of this transformation here in the chat.

After verifying the correctness of the first prompt, the next one instructs the LLM to create the Colab Python notebook that can be applied to the 60 csv files downloaded from INMET's manual weather station (the 30 years of data spanning 1991-2020).

PERSONA and CONTEXT:

You are a research assistant who will help me create a Python script to transform `csv` files following the steps given below. All `csv` files are attached to this chat.

TASKS:

1. The files are named as ‘`cyyyy-1.csv`’ and ‘`cyyyy-2.csv`’, where ‘yyyy’ is the year spanning from 1991 to 2020. There are two files for each year.

2. Join the two files in a single `csv` file. The single file should contain all data from 01/01/yyyy to 01/01/yyyy+1.

3. Keep only the fields `Data`, `Hora`, `Temp.`, `Temp. Max.` and `Temp. Min.` . The remaining ones can be removed.

4. Subtract 300 from the values under the field ‘`Hora`’ when the value is 1200 or 1800. This will convert these values to 900 and 1500 respectively. Furthermore, add 2100 to values equal to 0000 in the column ‘`Hora`’, making them equal to 2100. The heading for these values changes to ‘`Hora (UTC-3)`’.

5. Where values under column heading ‘`Hora`’ are equal to 2100, change the date for the day before.

6. Remove the rows that now have the previous and the next years in the beginning and at the end of the single file.

7. Now compute the weighted mean temperature using the temperature values from the 900, the 2100 time labels, as well as the maximum and minimum temperatures for each day. The formula to be used is: `TMC = (T09 + 2*T21 + Tmax + Tmin)/5`.

8. The resulting `csv` file for each year uses ‘;’ as field delimitator and ‘,’ as decimal point, and it will have the fields `DATA`, `TMAX`, `TMIN`, `T09`, `T21` and `TMC`.

3.2 Prompt to tranform `csv` files from the automatic station

The prompt to create the Colab Python notebook for the transformation of the automatic station data is presented next. The main objective is to first join all files and then obtain the daily mean temperature from the hourly values.

PERSONA AND CONTEXT:

- Act as a research assistant who is proficient with Microsoft Excel.
- Your task is to transform meteorological data files (`csv` format) from automatic stations for the purpose at hand.
- This task is part of an undergraduate project in climatology, where students will analyse temperature trends for a given location.
- The transformation will be given in sequential steps so you can create a Python script that will do what is desired within the Google Colab environment.
- Filenames follow the rule: `ayyyy-1.csv` and `ayyy-2.csv`. The '`a`' serves to indicate the file is for the automatic station. The '`yyyy`' gives the year that may vary between 2018 and 2026. The '`-1`' or '`-2`' tells if the file contains the first 6 months of data or the last 6 months of data for the given year.

TASKS and EVALUATION:

1. the script needs to join all `ayyy-1.csv` and `ayyy-2.csv` sequentially in one single csv file named '`a5anos.csv`'
2. the '`a5anos.csv`' file should keep only the first 3 columns of data with the fields DATA, HORA (UTC) e TEMP. INST.. The remaining fields can be removed.
3. add 2100 to the data labeled with HORA with the values '0000', '0100' and '0200', and change the label DATA to the previous day in these rows.
4. subtract 300 from the data withing the HORA field with the values '0300', '0400', '0500', etc. until '2300', but keep the same DATA in these rows.
5. obtain the mean daily temperature in the '`a5anos.csv`' file, store this daily mean temperature in the first row for each day (tied to the '0000' time) and remove the other rows. Moreover, you can remove the column HORA, leaving the '`a5anos.csv`' file only with 2 columns: DATA and TEMP. MÉDIA DIÁRIA
6. show a preview of the '`a5anos.csv`' file in this chat

3.3 Graphical output

After Gemini's sessions and the subsequent workflow in Google's Colab, the resulting `csv` files are merged in a single spreadsheet to plot the time series of temperature anomalies. As this final step includes the two trend calculations, students have a spreadsheet template to put their data. A time-series example is shown in figure 2. In this case, even though the slope is small (0,0003), Spearman's correlation $\rho = +0{,}1121$ confirms the slight warming trend.

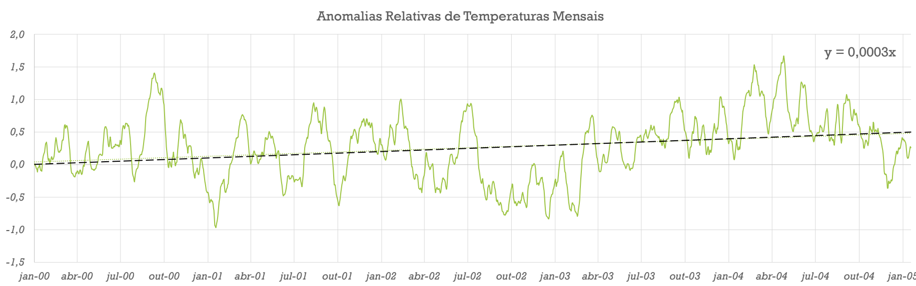

Fig. 2 A sample time series for temperature relative anomalies in Maringá, Brazil. The linear trend is shown indicating a slight warming during the period.

4 Discussion and Conclusions

Artificial intelligence is certainly becoming a game changer in many aspects of higher education, particularly in the engineering field. It is now possible to implement learning activities that use computer coding without the need to climb a steep learning curve. AI is allowing new approaches of engagement in problem-based learning [13] as well as with basic content [14]. These initiatives bring college education closer to more personalized support for students [15].

We followed a three-pronged strategy in the climatology class when proposing this activity, and AI was key to the implementation. Some tradeoffs had to be made to ensure a successful experience. For example, the choice of Gemini instead of a different LLM was made because it is part of the Google family of products. We tested Colab (which is also a Google product) with Python scripts created by a Microsoft-based LLM (Copilot), and found that it required more fine-tuning when compared to the Gemini-generated code. The issue of using a free or a paid version of the LLM needs to be considered since free AI agents place limits on how much natural language processing (NLP) is allowed in a given session.

The use of spreadsheets, AI prompt formulation, and collaborative programming aimed to decide whether a particular set of weather data indicated warming, cooling, or a neutral trend. The data were obtained from Brazil's National Institute of Meteorology and transformed using the aforementioned tools. In the end, a time series was constructed and two distinct trend metrics were calculated from the data: a linear regression estimate and a correlation coefficient. The data transformation involved many steps ranging from defining a naming scheme for the various files to obtaining the 30-year climatological normal from 1991 to 2020. Subsequently, temperature anomalies for the most recent 5 years of data were obtained.

This activity could hardly be attempted on a semester schedule without the help of AI. It cannot be denied that there is discomfort about its widespread use due to ethical concerns, new entrance requirements in the workforce, and high energy demand by data warehouses, to name a few. [16] warns about related issues, arguing that new ways of interacting with intelligent machines will have to be developed. [17] presents a more conservative view, discussing dualities such as natural vs. artificial and interpretation vs. explanation in AI systems. But we cannot forget that current college students are digital natives who have been using mobile devices since an early age. As faculty members, we cannot simply overlook this fact and pretend that university teaching does not face a new reality.

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