A Guided Comparison of Bioinstrumentation Laboratory Data Analysis using Mathematical Software and Generative AI

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***Abstract*—Generative AI tools are becoming more widely available and have increasing functionality. Students are beginning to integrate AI into their current practice and will need to be able to ethically use AI in their future careers. Instead of banning AI in an undergraduate biomedical instrumentation instructional laboratory course at a large public university, it was intentionally added with awareness of privacy, equity, and accountability. An assignment was adapted to walk students through comparing data analysis by hand, with mathematical software, and with generative AI. The goal of the updated assignment was for students to be able to think critically about the difference between doing analysis by hand, with purpose-built and validated software, and with a generic tool based on a large language model. The submitted post-lab assignments were analyzed by the research team to understand the students' approach to this assignment and what they learned about each method. All the students were able to complete the assignment, however there was mixed feedback on the usefulness of the assignment. Details about the assignment development and analysis of student work on the assignment are included in this paper.**

***Index Terms*—undergraduate, laboratory, generative AI, biomedical instrumentation**

I. Introduction

As generative artificial intelligence (GenAI) has become widely available and grown in popularity, discussions of the impact on education have followed. Faculty responses have varied from complete bans of GenAI to fully embracing the use of GenAI in their courses. Students have also varied in response from not using GenAI to using it for multiple aspects of their life including coursework. Ultimately, students will need to be able to ethically use AI in their future careers. With this in mind, a post-lab assignment was modified to guide students through completing the same data analysis using three techniques: by hand, with mathematical software, and with GenAI. The goal of the updated assignment was for students to be able to think critically about the difference between doing analysis manually, with purpose-built and validated software, and with a generic tool based on a large language model.

This assignment is from a biomedical instrumentation laboratory that is required for students in the third year of a Bioengineering program at a large public university in the Midwestern United States. During the course, students design, build, and test several circuits to measure biosignals. In this laboratory experiment, students built two circuits to measure temperature: one with a silicon band gap sensor and one with a thermistor. After confirming that the circuits could measure the room temperature, students placed a cold pack on both temperature sensors and recorded the voltage change from room temperature to the cold pack temperature with an oscilloscope. Then exported the data as a CSV file using Keysight BenchVue, the software from the oscilloscope manufacturer.

In the original assignment, the students were asked to convert the voltage to temperature and plot the data in Excel. From that plot, they estimated the time constant and fit an exponential curve to the data by hand in Excel. The updated assignment also includes plotting and fitting the curve using MATLAB and a GenAI tool of their choice. After completing the task with each technique, the students were asked to compare the equations for each curve fit, the usefulness of those equations as a mathematical model for simulation, and reflect on the process of obtaining the equation in each scenario. All students were able to complete the data analysis with all three methods, however, the time taken to complete the analysis and the perceived usefulness of the comparison varied widely between students.

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II. Background

GenAI has the capacity to assist both students and instructors in higher education. For example, it can guide instructors in creating exercises, quizzes, and scenarios for student check-ins while for students it can act as a virtual tutor in learning and assessment while also providing an interactive and personalized learning environment [1]. However, these large language models (LLMs) tend to make mistakes with frequent inaccuracies and are best used to generate simple content to be reviewed and adapted. Therefore, it is important to use these LLMs carefully when they are inevitably combined with engineering education [2]. Integrating LLMs into education must take into account the privacy and security of its users along with ethical and equitable access to accredit human critical thinking [3].

The recent release of sophisticated generative AI models capable of generating text and responses similar to a human has led to both interest and concern in higher education. LLMs like ChatGPT have the potential to improve efficiency by identifying patterns in large amounts of data, providing summaries of research literature, and writing or debugging code. However, it has also led to concerns of dishonesty in higher education, with students using LLMs to generate essays for assignments and the possibility of AI-generated research papers infiltrating academic journals. The *Science* family of journals now specifically prohibits the use of AI-generated text or figures in research publications, stating that AI-generated content is not original work. Since there is little transparency in regards to the data that LLMs like ChatGPT are trained on, biases within training data can lead to factual errors, misrepresentations, and a lack of proper citations [4]. At the same time, as this technology continues to develop, it has the potential to significantly improve efficiency and encourage student assessment that relies on the development of robust critical thinking skills. Therefore, students must learn to use generative AI and LLMs as a supplementary tool while understanding their natural limitations and inherent biases [5]. In this way, students will be prepared for the ethical and effective use of generative AI in their future academic and industry careers.

Writing an accurate and well-organized lab report is the foundation of undergraduate science education. However, the high-performance expectation and the time-consuming nature of this process have students searching for quicker alternatives, such as GenAI. From simple calculation aid to drafting whole lab reports, GenAI has become a frequent tool for students.

Researchers have analyzed ChatGPT in chemistry labs to assess its ability to develop high-quality lab reports. They investigated three aspects: calculations and data analysis, the depth of the analysis, and proficiency of the introduction and concluding statements. Overall findings indicated that ChatGPT could handle simple calculations but often failed to solve complex chemistry problems, such as calculating statistics from a given data set. Even when creating a well-written concluding statement about those statistics, the analysis lacked depth past broad generalizations. ChatGPT cited fake scientific literature, using relevant-sounding titles, to support its claims [6]. With ChatGPT, writers are relieved of simple computing tasks but at the cost of surface-level analysis within lab reports. ChatGPT could be used to allow for more focus on interpreting data and critical thinking on core concepts [7].

III. Methods

The context of the laboratory course, how the adapted assignment was developed, and how the student worked was assessed are discussed in this section.

A. Course Context

The course is a two-credit hour, semester-long, undergraduate laboratory in biomedical instrumentation. There is a corresponding lecture course that is three credit hours, and it is taught by a different instructor. Both courses are required for all bioengineering undergraduate students. It is also taken as a technical elective in majors from across the College of Engineering.

The total enrollment in the laboratory course was 68 students in the spring 2024 semester. Each Monday students meet for a one-hour, common introduction lecture with the faculty member assigned to the course. Then the students complete the experiment, usually in pairs, during a scheduled three-hour lab section later in the week. There were 34 teams of two during the spring 2024 semester.

Each of the laboratory sections has a graduate teaching assistant assigned to teach the laboratory course. The experience level of the graduate TAs varies each semester. Additionally, each laboratory also has an undergraduate assistant to help with questions from students. All of the undergraduate assistants have completed the course within the last two semesters. The faculty member is available during each lab section and periodically checks in on the progress of experiments.

There are 12 complete lab stations in the lab space. Each station has a function generator, oscilloscope, DC power supply, digital multimeter, a DAQ, and a desktop computer with Windows 11 and necessary software installed. All the necessary components to build a circuit for each laboratory experiment are provided along with a solderless breadboard. For each of the assigned laboratory experiments, students complete an individual pre-lab assignment, a group post-lab worksheet, and an individual post-lab reflection.

B. Assignment Development

In the original assignment, students follow a protocol and circuit diagram to design and build two different circuits to measure temperature. One uses a silicon bandgap sensor while the other uses a thermistor. Students validate both circuits by ensuring that they can accurately measure the room temperature. The sensors are then placed in contact with a cold pack to measure the resulting change in voltage using an oscilloscope. Voltage data over time is exported into a CSV file using the Keysight BenchVue software from the oscilloscope manufacturer.

In the post-laboratory assignment, students used the equations they derived from sensor datasheets during the pre-lab assignment to convert voltage data to temperature in Microsoft Excel. In the original assignment, they used Excel to estimate the time constant, plot the data, and fit an exponential curve to the data. They used the generated curve fits to draw conclusions about each sensor's capabilities and limitations. In the updated assignment the students were also given additional tasks to plot and generate a curve-fit for the data using MATLAB and a generative AI tool of their choice. A GenAI tool was not specified in the assignment to allow students to use a tool they were comfortable using based on their criteria (e.g., cost, privacy, familiarity). Students were then asked to compare the resulting equations and the relative ease of obtaining an equation for each method. The post-laboratory reflection asked students if they understood the difference between the two temperature sensors and what they learned from comparing techniques to generate mathematical models.

At the time of creating this assignment many AI tools that were tested only provided suggestions of other software for the task or proposed Python code to complete the task. One free AI tool, Julius AI, was able to use data from an uploaded CSV, create a plot, and complete a curve fit.

C. Assessment

After the post-laboratory assignments were completed, the students' identities were removed from the assignments and provided to a research team not associated with the course this semester. The team reviewed the mathematical models, the students' comparison of the models, and their reflections. This analysis provided insight into the students' approach to the assignment and identified possible changes to the assignment in future semesters.

IV. RESULTS

First, the post-lab assignments were categorized by the GenAI tool selected by each student team. Table I provides a list of the generative AI tools that students used during this lab. The majority of students (85.3%) utilized a version of ChatGPT, which is divided into 3 categories based on student-provided information for version type, i.e. 3.5, 4, or not specified. Allowing the students to select a GenAI tool added complexity to the analysis. As part of their reflection, students were asked to compare the three methods for fitting a model to their data: by-hand calculation, the MATLAB Curve Fitter application, and a generative AI tool of their choice. Specifically, they were asked to identify which model was the easiest to create, and the hardest to create, as well as which models were the most complex and the simplest. A summary of the students' assessment for each question is provided in Fig. 1. The ease or difficulty of creation did not show great differences in student ranking, with each of the three modeling techniques being chosen almost equally by the students. However, the students did differentially rank the models that were generated based on their complexity, with generative AI and by-hand methods creating simpler models, while MATLAB was overwhelmingly chosen as the most complex model.

TABLE I
GENAI TOOL CHOSEN BY LAB TEAMS FOR FITTING A CURVE TO THEIR COLLECTED DATA FOR EACH SENSOR.

GenAI Used	Count	Percent of Total
ChatGPT (Unspecified)	15	44.12%
ChatGPT 3.5	8	23.53%
ChatGPT 4.0	6	17.65%
Claude AI	2	5.88%
COPILOT	1	2.94%
Curve.Fit	1	2.94%
Julius AI	1	2.94%
Grand Total	**34**	**100.00%**

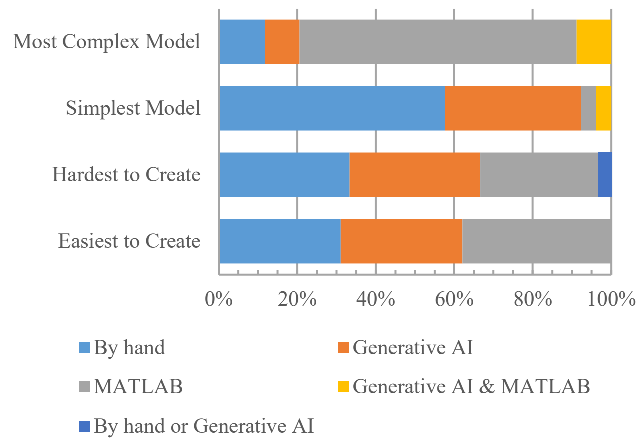

Fig. 1. Summary of lab team responses evaluating the three model techniques for the easiest to create, the hardest to create, the simplest model, and the most complex model generated.

To investigate this further, split the responses by what generative AI tool the students reported using. Fig. 2 displays the students' choices for the easiest model to create separated by what tool they reported using. Notably, the ChatGPT without a specified version showed that students thought by hand or MATLAB was much simpler to use than GenAI, while those who stated that they used ChatGPT 4.0, Claude AI, and Curve.Fit all reported that GenAI was simpler. These GenAI tools may have been easier to use or more purpose-built for curve and model fitting. Fig. 3 highlights a similar trend, where the students who used ChatGPT without specifying the model were most likely to report that GenAI was the hardest method to create a model. This may be due to the fact that the students who did not report a version of ChatGPT are less familiar with GenAI tools in general and did not have prior experience with understanding how to prompt the system to achieve their specific goals.

In most cases, the GenAI tool provided code that needed to be executed in another software application to complete the curve fit. Of the 30 lab teams that reported generating code, 16 had the GenAI tool create MATLAB code and the

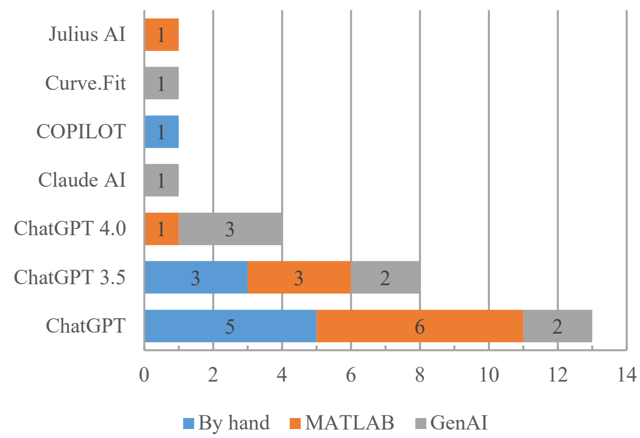

Fig. 2. A breakdown of lab teams' selection for the easiest model to create separated by what generative AI tool they reported using. Numbers represent the number of students (total n = 29 responses)

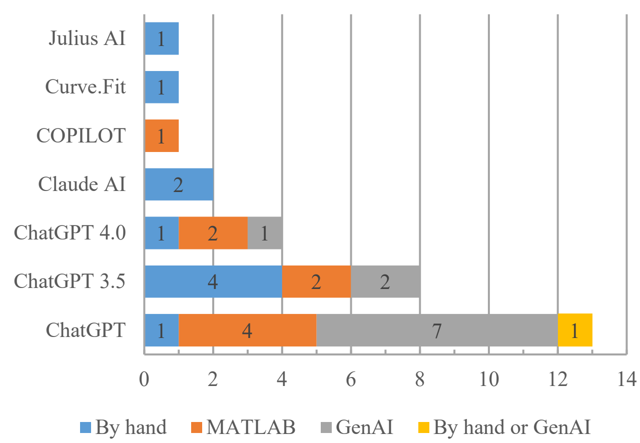

Fig. 3. A breakdown of lab teams' selection for the hardest model to create separated by reported generative AI tool. Numbers represent the number of students (total n = 30 responses)

other 14 teams had it generate Python code. For the teams that used the GenAI tool to create MATLAB code, they created unintended redundancy in the GenAI portion of the assignment. However, one student reported that "ChatGPT was also difficult to work with, but after switching from python [sic] to MATLAB things were much easier, as I don't know how to run python [sic]." Therefore, while redundant, the language choice was likely a matter of student preference. Additionally, having GenAI create MATLAB code could have clouded the students' reflections of the ease of creating models and their complexity because of the redundancy in the use of MATLAB for both parts.

While the stated hypothesis was that the cold pack data was an exponential decay, some lab teams did not generate an exponential curve fit with GenAI. Other curve fit equations included linear, polynomial, and two-term exponential models.

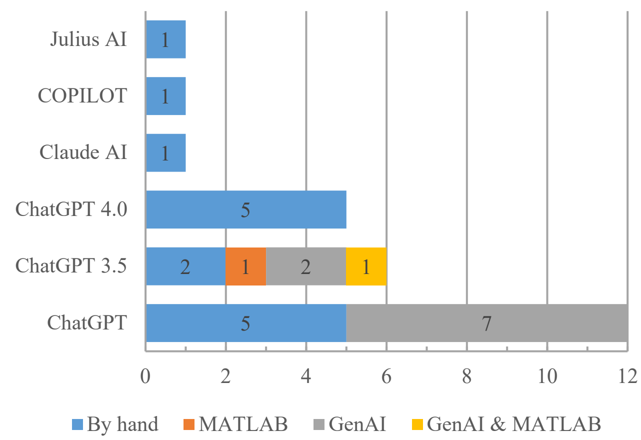

Fig. 4. A breakdown of lab teams' selection for simplest model separated by reported generative AI tool. Numbers represent the number of students (total n = 26 responses)

For both MATLAB and GenAI, the degree to which the generated model resembled the data was dependent on the equation parameters provided. For example, simply changing the model from `y = a*exp(b*x)` to `y = a*exp(-b*x)+c` yields very different outputs because of the default starting options of the fit function in both MATLAB and Python. Additionally, since the experiment instructions provided to fit the data by hand to the equation $y = \Delta T e^{-t/\tau} + b$, the similarities of the by hand model to those created by MATLAB and GenAI might not have been realized because of the model provided.

The next questions addressed the complexity of the model equations that were generated by each technique. In Fig. 4, students ranked the by-hand method as the least complex equation, followed by the generative AI model. Fig. 5 shows that students were most likely to select MATLAB as generating the most complex model equation. Since each method fit a curve to the same data, all three equations should have the same level of complexity. However, the by-hand and Gen AI options required more user input and finessing to increase the fit of the model than the purpose-built Curve Fitter app in MATLAB, explaining why more students were able to achieve their most complex model in MATLAB.

Student responses to reflection questions revealed both frustration and interest in the integration of GenAI in the post-laboratory assignment. Many students expressed frustration with the amount of time it took to use GenAI for curve fitting, they mentioned not knowing enough about GenAI to understand how to approach certain issues or fine tune their model. For instance, two students noted that the use of GenAI was "definitely challenging for us and not similar to anything I have done before in my other classes" and "I was not familiar with these methods and more practice could help me improve on these topics." Students also mentioned that it was difficult to understand each AI tool's limitations and found adjusting the AI model "finicky." One key piece of student feedback was that "it should not be an assumption that students already

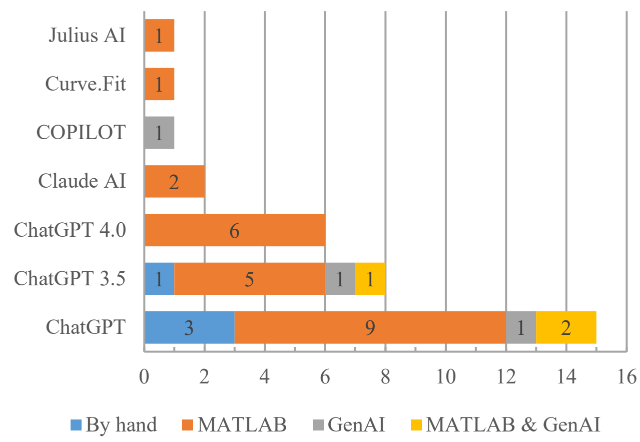

Fig. 5. A breakdown of lab teams' selection for complex model separated by reported generative AI tool. Numbers represent the number of students (total n = 34 responses)

know how to use this technology with no training and no additional information from the lecture slides and lecture that was provided." However, despite frustration and difficulty, many students also had positive opinions, noting that they "enjoyed the mathematical modeling with artificial intelligence and matlab [sic]" and "generative AI is something I have been wanting to explore more, so this was an intriguing part of the lab for me."

Many students also described their troubleshooting process and an understanding of how "some approaches are easier and are better suited to different forms of data analysis." But final takeaways differed, some mentioned that GenAI "took a lot more effort to find the right prompts to ask than figuring out the Matlab [sic]" and "took a long time to figure out the errors." Others "learned that using software was pretty efficient at creating a model." The most positive impression from reflections stated that "if you know how to use the tool, any of them can work effectively. ChatGPT and the Curve Fitter application in MATLAB both had almost identical models to fit the data collected in lab, but it was because I knew what I was looking for and could guide both of the tools to give me the correct answer."

V. Discussion

Overall, the results of student work and reflections seem to indicate that the integration of GenAI was interesting and novel, but came with frustration for many students. The struggle to troubleshoot and fine-tune models helped students think critically about the strengths and limitations of analyzing data by hand, with purpose-built software, and with large language model tools. However, in many cases, student unfamiliarity with GenAI tools may have caused the assignment to take significantly more time than anticipated and led to a general assumption that these tools cannot be used effectively for more complex tasks such as data analysis. Overall, the varied approaches and difficulties experienced did not lead all teams to meet the intended goal of critically thinking about the differences in model creation with all three models. A course staff member suggested that perhaps moving the GenAI part of the assignment to a demonstration and having a more guided discussion about the three methods during the lecture may be more effective in the future. This guided format might lead to a deeper understanding of the benefits and limitations of each method [8].

The manner in which GenAI models are trained makes them very sensitive with wording, which creates a learning curve for users in understanding how to effectively craft prompts to get expected output from GenAI [9], [10]. From these results, it would be interesting to see how student attitudes might change if they were provided with resources or lecture content on how to best prompt GenAI to obtain more reliable model results. Providing students with examples where AI tools were successfully used in similar contexts could help bridge the gap between theoretical knowledge and practical application [8], [11], [12]. Additionally, prompts of more successful teams from this semester could be analyzed to provide prompt creation tips in future semesters. One potential change could be for students to use GenAI to create a protocol or estimate of the curve fit model, and then use that as a basis for fine-tuning the model in MATLAB or by hand in Excel [12].

The takeaways from this assignment for both the students and the instructor were limited by the design choices. First, by allowing the students to select a GenAI tool, an additional variable was added to the analysis. Second, the time it would take for students to learn about and complete each method was underestimated and led to frustrations that distracted students from the goal of the assignment. Finally, the content of the post-lab reflections was limited based on the prompts given to students. The specific prompt did not allow researchers to analyze what each student understood about the benefits and limitations of each method. Each of these design choices will be reconsidered in future assignments.

Given the evolving nature of AI tools, continual updates to the curriculum and assignment designs are essential to keep pace with technological advancements. Regular feedback involving students and educators will be crucial in refining these educational integrations, ensuring that they remain relevant and effective in enhancing both the learning process and the outcomes. For example, since creating this assignment, updates to ChatGPT have allowed the uploading of spreadsheets and MathWorks has created a MATLAB GPT with integration between ChatGPT and MATLAB Online. These new features and others will also be explored for future iterations of this assignment.

VI. Conclusions and Future Work

Overall, this first implementation of an assignment with GenAI had mixed outcomes. All of the lab teams generated a curve fit with all three methods. However, based on the reflections submitted, it does not seem that all teams fully understood the benefits and limitations of each method.

Each team had a wide variety of prior knowledge of each method which led to widely varying times to complete the assignment. Additional analysis of the student reflections and GenAI prompts is planned. Based on student feedback and new advances in GenAI the introduction lecture and post-lab assignment will be modified in future semesters.

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