[Result, but poetic]: Does LLM Use Improve Data Science Education?*

Evidence from a Canadian Undergraduate Statistics Course

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August 2, 2024

An abstract should eventually go here!!

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*Code and data are available at: https://github.com/lcarnegie/llms-achievement.

1 Introduction and Literature Review

The wide release of ChatGPT and other Large Language Models (LLMs) has rapidly transformed education at all levels and disciplines, creating excitement and apprehension among educators and students alike. They offer unprecedented support for student learning in tasks ranging from writing assistance to support in complex problem-solving, with the potential to enhance academic performance and student outcomes. At the same time, their use raises important questions about academic integrity, the development of critical thinking skills (particular in undergraduates), as well as questions about their implications for effective learning overall.

The potential for LLMs to positively affect students' academic performance in data science can be clearly inferred from already-demonstrated effects on adjacent professional fields. The tasks involved in a data science workflow can be generally broken down into two key competencies. The first is programming, which is done when cleaning, analyzing, visualizing data using languages like R or Python. The second is writing, which is primarily done when communicating results. There is experimental evidence from adjacent professional fields that LLMs can improve productivity in both of these competencies.

Peng et al. (2023) show the potential impact of LLMs on students' computer programming skills, through their uncovering of the significantly positive impacts of GitHub Copilot (an LLM-powered programming assistant) on the productivity of computer programmers. In an experiment involving 95 freelance programmers, they found that that programmers with access to Copilot completed a standardized programming task 55.8% faster than the control group. Crucially, it was found that programmers with less experience saw the greatest improvements in productivity. Given that programming is a core component of data science practice, this suggests that these benefits could reasonably carry over to students in data science courses as well.

Dell'Acqua et al. (2023), while primarily about management consulting tasks, provides evidence that LLMs can significantly improve writing productivity. In a field experiment involving Consultants recruited from the Boston Consulting Group (BCG), they found that the use of GPT-4 in the experimental group led to a 25% increase in delivery speed of business tasks (most involving some writing), as well as a 40% increase in human-rated performance on those tasks. Similar to computer programming, these productivity increases were most pronounced for those with below average performance, with their output increasing by 43%. Though not all tasks done using AI saw the same productivity improvements, the authors expressed particular optimism for LLMs' potential to generally expedite menial knowledge-work tasks. These included tasks such as generating new ideas and creating persuasive and informative writing - both examples directly apply to data science education through their analogues of coming up with project ideas and writing more engaging reports. As a whole, they show that LLMs could equally augment the quality of student writing and course projects in data science as well.

Clearly, the implications of these case studies appear promising. However, literature from educators both adjacent to and distant from statistics and data science suggest much more varied perspectives on how LLMs can impact student performance.

Valenzuela et al. (2024) argue that LLMs lead to a loss of serendipity (which leads to less original work) and de-skilling (primarily with respect to programming ability), among other consequences. These particular outcomes could negatively affect students' effective learning of data science. On the other hand, Ellis and Slade (2023) take a more optimistic perspective, taking the popular stance of comparing ChatGPT to previously controversial learning technologies like calculators. They argue that LLMs are just another technology that will impact Statistics and Data Science education like the calculator did. However, they take a broader perspective on the issue and more specific inquiry could be done in how effective LLMs are at improving student outcomes within data science education in particular.

In a similar attitude, Tu et al. (2024) acknowledge that for students, LLMs can streamline many parts of a data science workflow - with that in mind, they suggest that data scientists in training should shift their self-perspectives from primarily being an analyst to primarily being a manager responsible for strategic oversight of the analysis. Crucially they emphasize that in both education and practice, LLMs and human intelligence should play complementary roles.

The simultaneous caution and interest the literature expressed toward using LLMs in educational settings was further corroborated by empirical studies on K-12 and university students as well.

At the high school level, Lazar et al. (2023) conducted a informal survey of secondary school teachers and students on their opinions of ChatGPT, they found that while LLMs could help spark creativity, provide academic support when teachers were unavailable, and model certain types of writing well, teachers were also cognizant of LLMs potential to limit students' learning in certain ways through overreliance. Beyond academic integrity concerns, teachers had similar concerns to Valenzuela et al. (2024) about de-skilling and an overall loss of agency in writing and critical thinking.

Cahill and McCabe (2024) surveyed undergraduate Political Science students on their attitudes toward and usage of AI tools. They found that the use of ChatGPT (among other machine-learning-powered software) was widespread. However, they also found that many students lacked the confidence in using AI for academic purposes - in particular, only 11% 'strongly agreed' that they know how to use AI to improve their writing. Like educators, students have nuanced views on appropriate AI use. In particular, respondents found that using it to writing whole papers as inappropriate, while using it for basic tasks like general assistance, writing feedback and basic data visualization was perceived more appropriately. Interestingly, first-generation college students were found to be more likely to use AI in their work, particularly in writing papers and helping with assignments. Their findings suggest that LLMs and other AI tools could be an equalizer for disadvantaged students. Rhough only political science students

were surveyed, statistics and data science students could reasonably have general attitudes that are similar.

As we have seen, the existing inquiry by educators has explored the general qualitative usage and student perceptions on these tools. Though informative, a key question still remains: how can students' academic performance be affected, precisely, through allowing them to use LLMs in classwork?

This paper aims to fill this gap by quantitatively investigating the relationship between students' grades and measures of student LLM usage and their attitudes toward LLMs in general, using evidence from a third-year undergraduate statistics course at the University of Toronto. Through examining how students interact with and perceive LLM tools and how these variables translate into student outcomes, the effects of LLM integration in data science education can be more precisely determined.

The remainder of this paper is structured as follows: Section 2 visualizes and analyzes survey data and coursework from students; Section 3 models the unstructured data to approximate a relationship between grades and usage/attitudes; Section 4 describes and analyzes the model's results; Section 5 discusses the implications of the findings for data science education and future research and practice in this rapidly evolving field.

2 Data

2.1 Background and Collection

To investigate students' usage and attitudes toward LLM use and how they related to their academic performance, a dataset containing their usage/attitudes, coursework, and academic performance was constructed. Data was sampled from the cohort of students taking STA302 - Methods of Data Analysis I, taught by one of the investigators in the Winter 2024 semester at the University of Toronto. By virtue of pre-requisites needed, this restricted the data collected to be only on upper-year undergraduate students.

Data was collected from students through an optional end-of-course survey. Whether or not they consented to their data being used in this investigation, all respondents received a +1% increase in their final course grade for their participation. All consenting responses were then cross-referenced to their course grade, as well as the GitHub account they used to complete their course research papers. The responses were finally anonymized by removing any personal references to the students themselves.

2.2 Cleaning and Variables of Interest

All the data was cleaned using R (R Core Team 2023) and it's tidyverse (Wickham et al. 2019), janitor (Firke 2023) and stringr (Wickham 2023), then tested for issues using the testthat package (Wickham 2011). This led to a final dataset containing 121 unique responses to 18 survey questions.

2.3 General Information

First, general information about the sample of students was derived first, through visualizing the basic data about them. This was done using the ggplot2 (Wickham 2016) package.

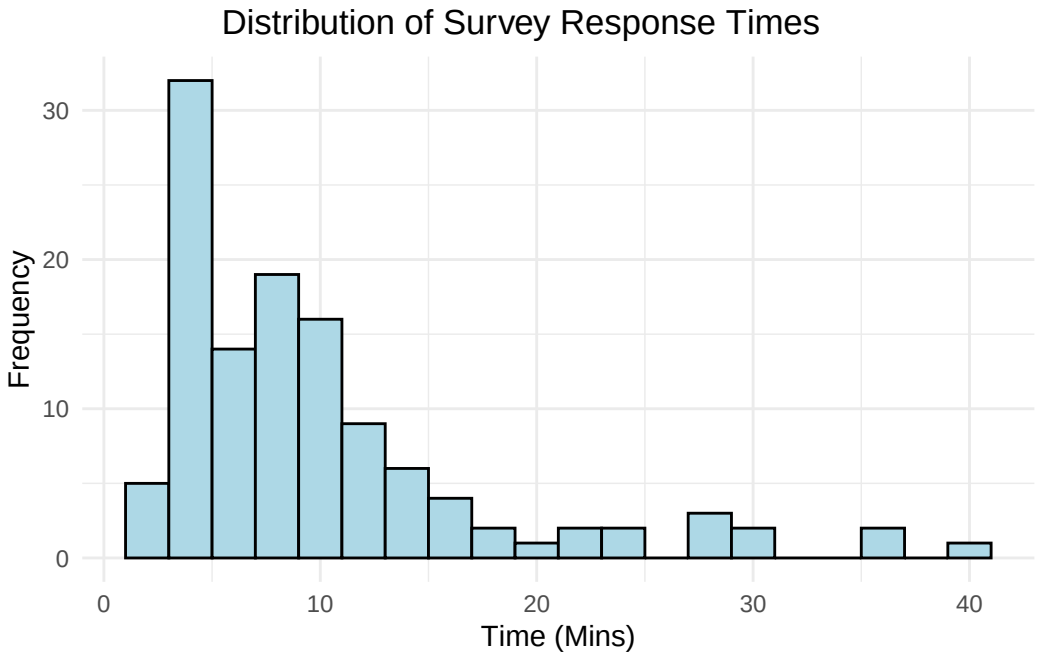


Figure 1: Distribution of Survey Response Times

Figure 1 shows the distribution of response times to the end-of-course survey. Respondents who consented generally took between 0-40 mins to answer all of the questions, with most response times ranging between 2-10 minutes. There was one consenting respondent who took 4308 minutes, whose observation was dropped from the visualization. Overall, however, this suggests that students generally took a meaningful amount of time and thought to engage with the survey's questions.

Figure 2 shows a wide distribution of student GPAs, with the majority clustering around a B (3.0/4.0) average. One factor possibly affecting the range is the course being a required course

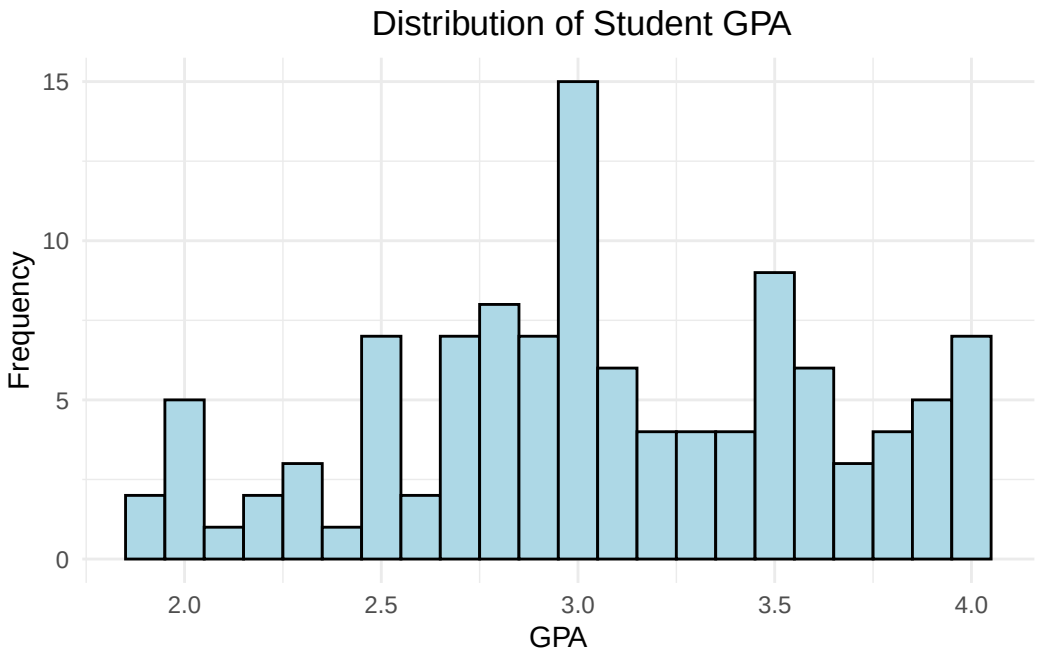


Figure 2: Distribution of Student GPA

Table 1: Count of Students by Year

2nd	3rd	4th	5th+
4	63	49	5

for programs in the Statistics, Mathematics and Computer Science departments. Though programs in these departments generally attract high-achieving students, some may still struggle. Another factor is that these GPAs were self-reported, which introduces some ambiguity - students may have provided either their cumulative GPA or their most recent term's GPA, or could have misreported it entirely. Despite these two factors, the diversity in reported grades suggests the course attracted students across a broad spectrum of academic performance levels.

We can also see in from Table 1 that students from a range of years took the course. That said, the majority of students were more senior undergraduates in their 3rd or 4th year of study. This makes sense, given the course's prerequisite of general statistics, which is a two-course sequence typically completed by students in their second year.

Programs of study [did something; waiting on major/minor data], as we can see in Figure 3...

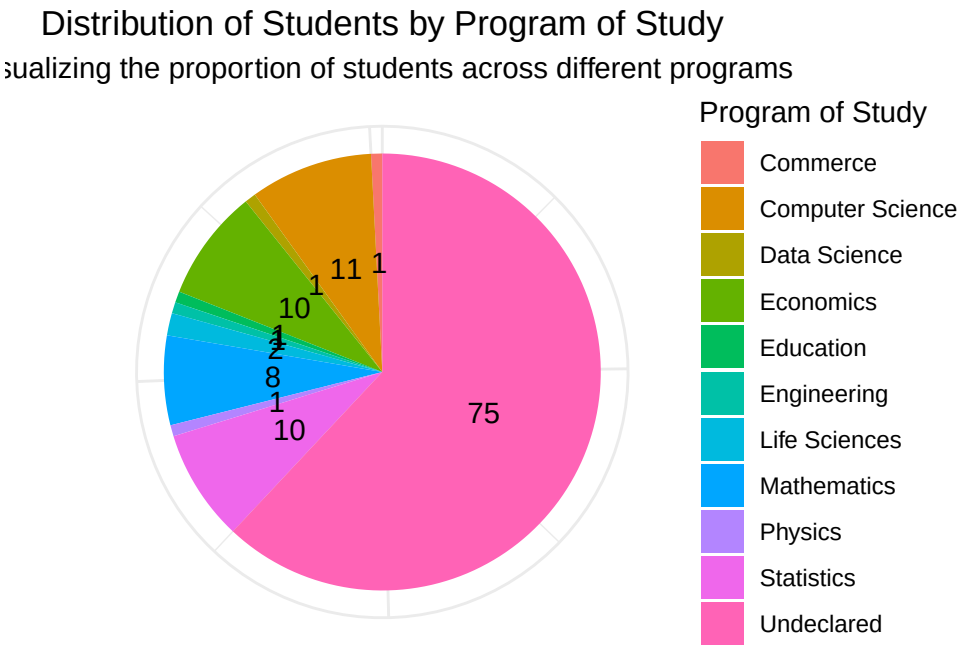


Figure 3

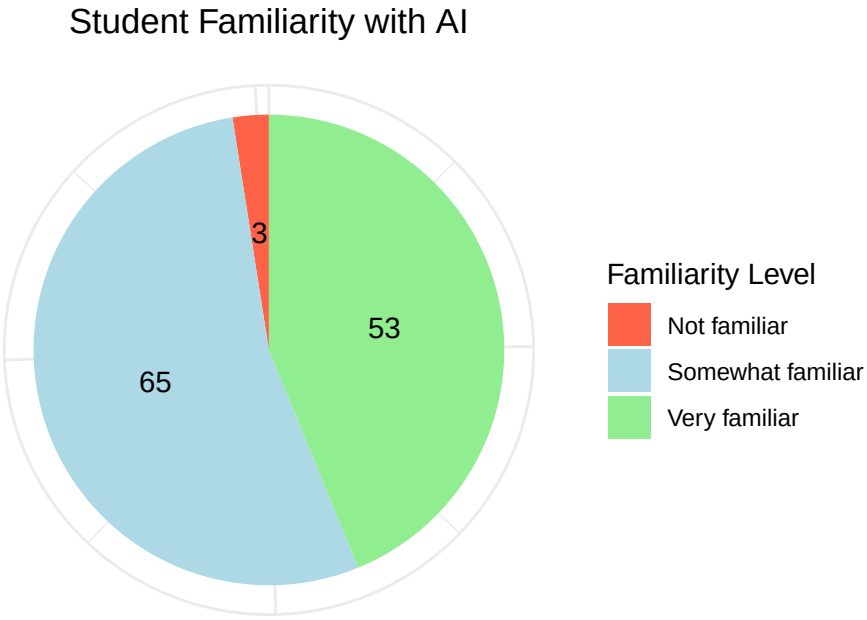


Figure 4: Student Familiarity with AI

2.4 Student Attitudes

Just as Cahill and McCabe (2024) found, the vast majority of students taking the course were at least "somewhat familiar" with ChatGPT and other LLMs. However, this vast over-representation of familiarity could be driven by the fact that the course is primarily targeted for students in Statistics, Computer Science, Economics, Mathematics and other quantitative disciplines, leading to a sample that is skewed to being more interested in computing in general.

Students were then asked about their attitudes and self-perception on writing and coding. First, students had varied attitudes toward their writing and their writing abilities in general, as seen in Figure 5 and fig-writing-multibar-2.

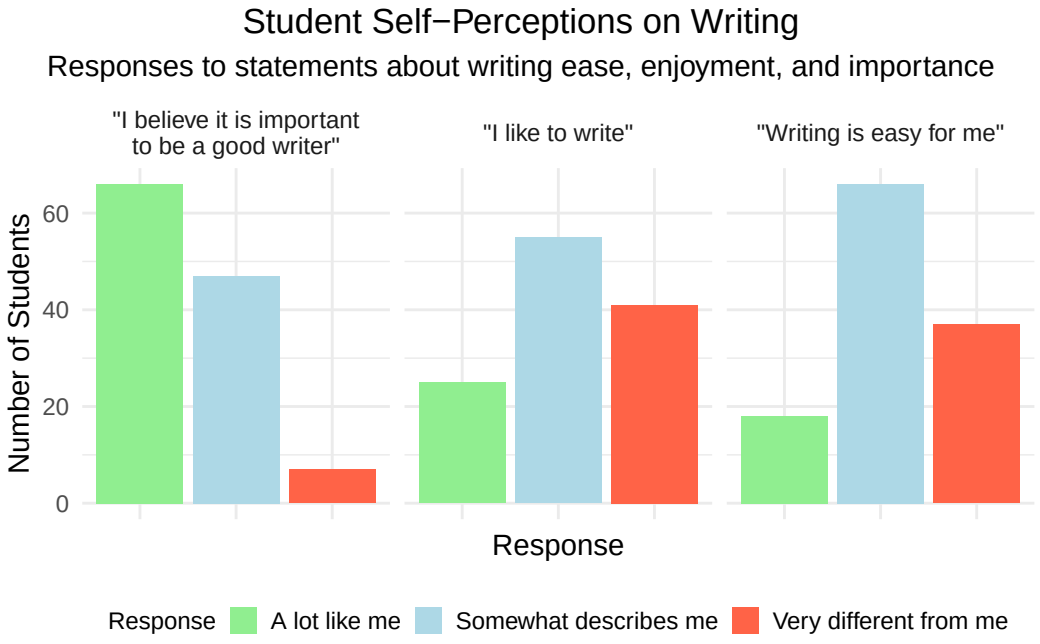


Figure 5

We can see in Figure 5 that most students believe it is important to be a good writing, though most are either indifferent or do not really like to write. In parallel way, students also do not find writing to be particularly easy, which could feed into the relative antipathy toward writing in general.

Mirroring this, Figure 6 shows that most students in the class were at least somewhat confident in their own writing abilities, but a significant contingent felt otherwise. Interestingly, although few students felt that they were confident writing ability, more felt that they were able to catch their mistakes, which could indicate a disconnect between how students perceive their work and how the work was actually evaluated.

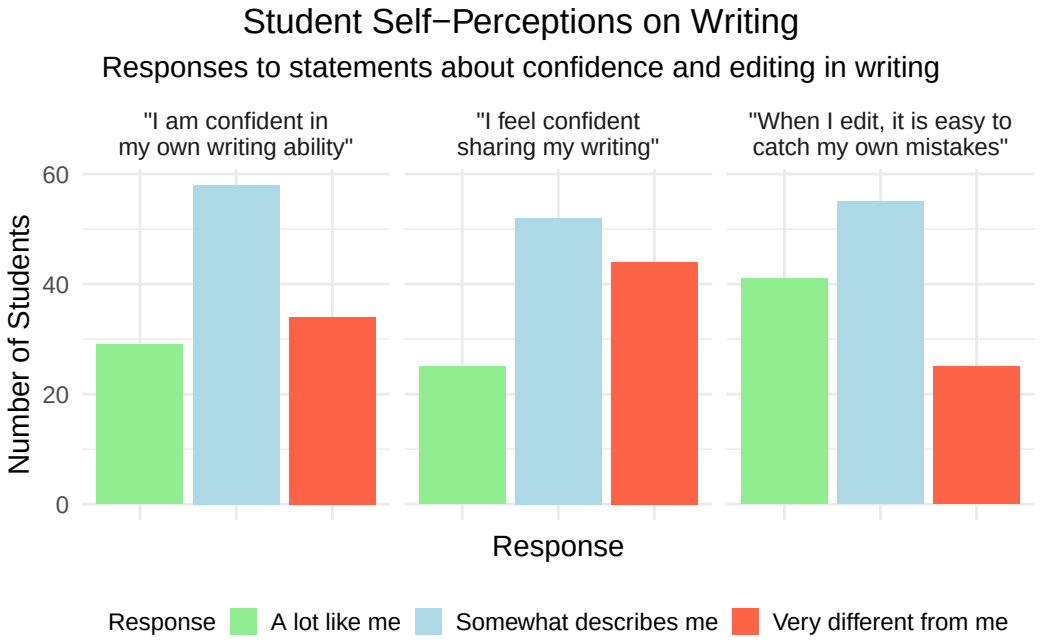


Figure 6

Students' self-perceptions about their coding abilities, shown in Figure 7 and Figure 8, also shed light on how students perceived themselves with respect to coursework, as R programming was a significant component of the course.

Figure 7 shows that student self-perceptions regarding coding proficiency and importance varied. There was strong consensus on the perceived importance of coding skills, with a majority of students strongly affirming this belief. However, students' self-assessed coding abilities and enjoyment are more heterogeneous, with a substantial proportion reporting moderate rather than high levels of ease and enjoyment in coding tasks. These findings suggest a complex interplay between students' recognition of coding's significance and their personal experiences with programming activities.

Figure 8 reveals a predominant moderate level of confidence among students in their overall coding ability, willingness to share code, and capacity to identify errors. Notably, students express slightly higher confidence in detecting their own coding mistakes compared to general coding ability or code sharing. These patterns suggest that while students have developed some coding self-efficacy, there is still considerable potential for enhancing their perceived competence and comfort across various coding-related activities.

Though students' self-perceptions around writing and coding are varied, there was strong consensus that the use of student AI tools is appropriate within an academic setting. One

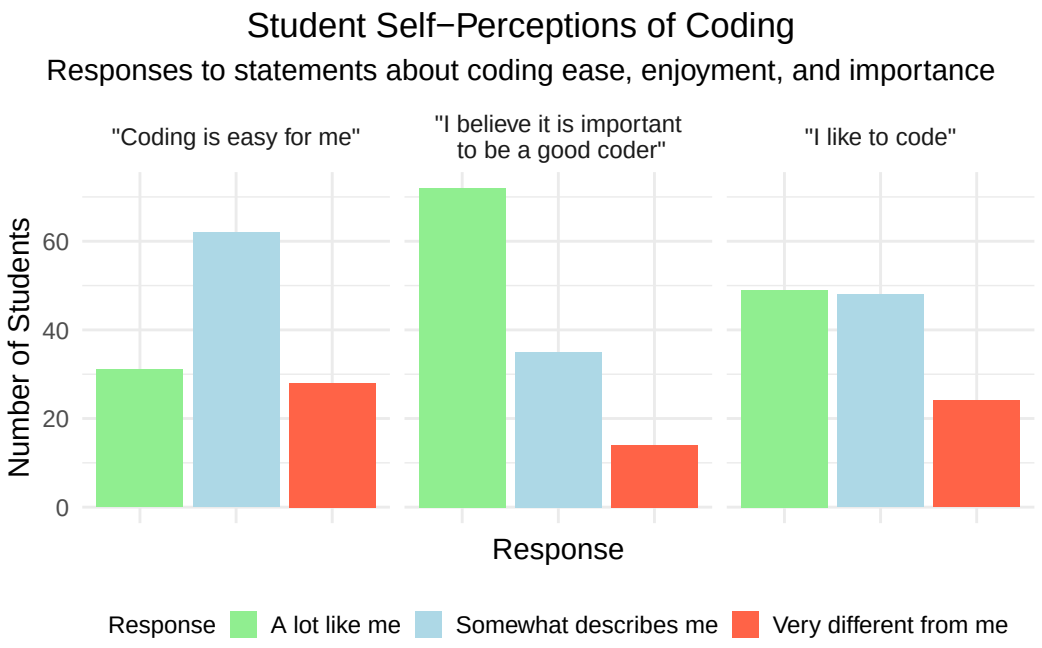


Figure 7

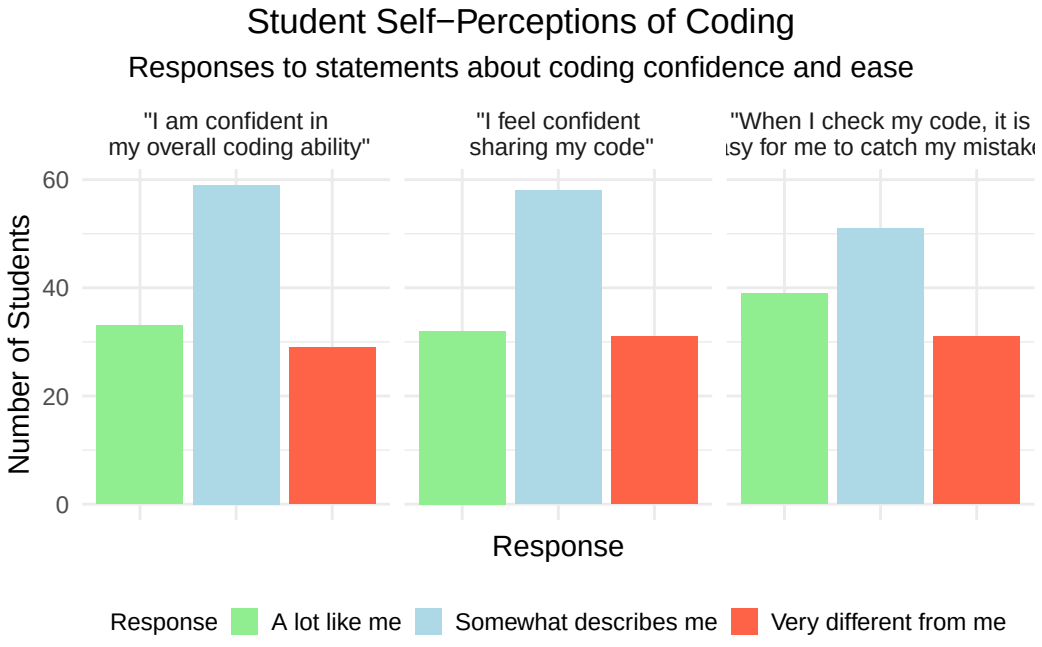


Figure 8

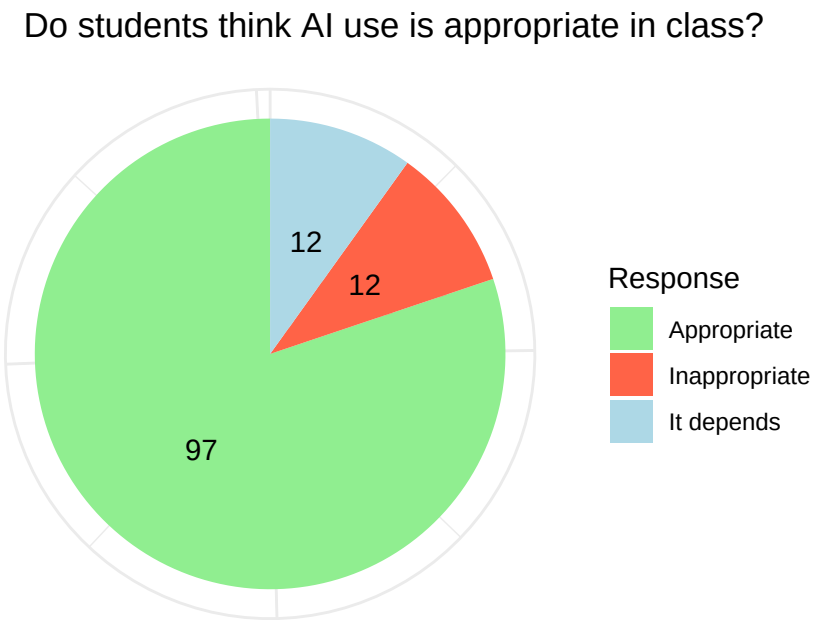


Figure 9

thing of note is that most who responded "It depends" generally found artificial intelligence tools to be appropriate, though with certain guidelines and rules governing their use.

2.5 Student Usage

To understand the role of AI chatbots in learning, students more granularly identified their usage by checking off various pre-defined use cases in the survey. Figure 10 shows that technical questions and explaining concepts were the two top use cases among students in the course. More than half of students also used ChatGPT for quick questions, general knowledge, writing paper code, and checking solutions. Just less than half used it to write paper content, which could suggest that students do not feel confident using it to improve writing, concurring with student attitudes expressed in Cahill and McCabe (2024).

2.5.1 Task-Specific Attitudes

Make a grid of all the tasks, with

Students were also asked to rate the helpfulness of LLMs on various tasks assigned during the course on a 4 point scale of "Did not use" to "Very Helpful". To simplify the presentation, responses were grouped into two main categories: "Less Helpful" and "More Helpful." The

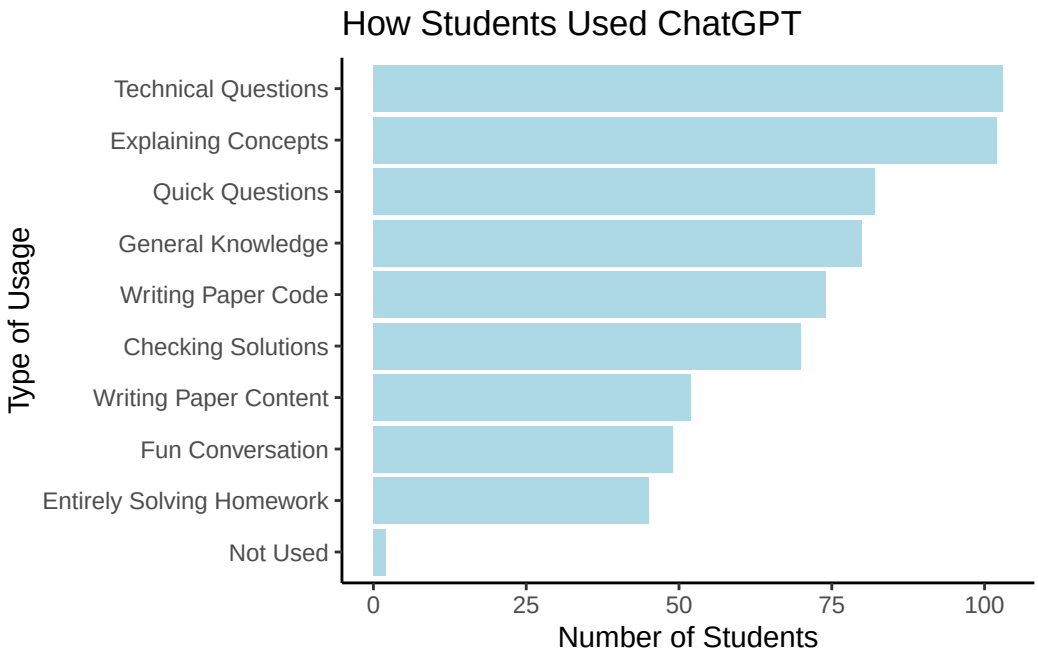


Figure 10: How Students Use ChatGPT

"Less Helpful" category combines responses where students found the AI either "Not helpful" or did not use it for the task, while the "More Helpful" category includes responses where the AI was considered "Somewhat helpful" or "Very helpfu

Figure 11 shows insights about how students used LLMs within the course. While most tasks were about split between students finding LLMs helpful or not, it was clear that they were most helpful in generating code. In the context of the course, this meant generating R code for transforming, analyzing, and visualizing data. To a lesser extent, students also found LLMs to be helpful in improving the existing writing they had, while not favouring it for writing content from scratch.

2.6 Sentiment Analysis

We then performed basic sentiment analysis on the open-response comment questions asked to students. To perform this text analysis, the tidytext package (Silge and Robinson 2016) was used.

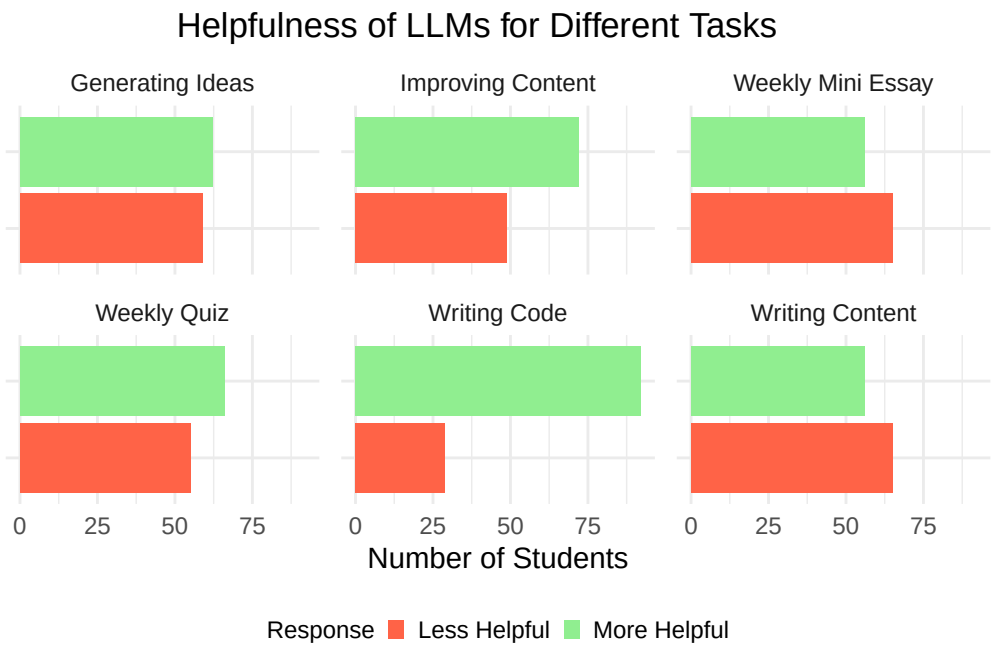


Figure 11: CHANGE/REMOVE

2.6.1 Appropriateness of AI in Schoolwork

In the survey, students were asked to provide an open-ended response to the question: "Please elaborate on to what extent do you think using generative AI tools such as ChatGPT by OpenAI (or equivalents) is ethical and appropriate for schoolwork?". These responses were attempted to be understood thematically.

Based on the word cloud and the relative counts of

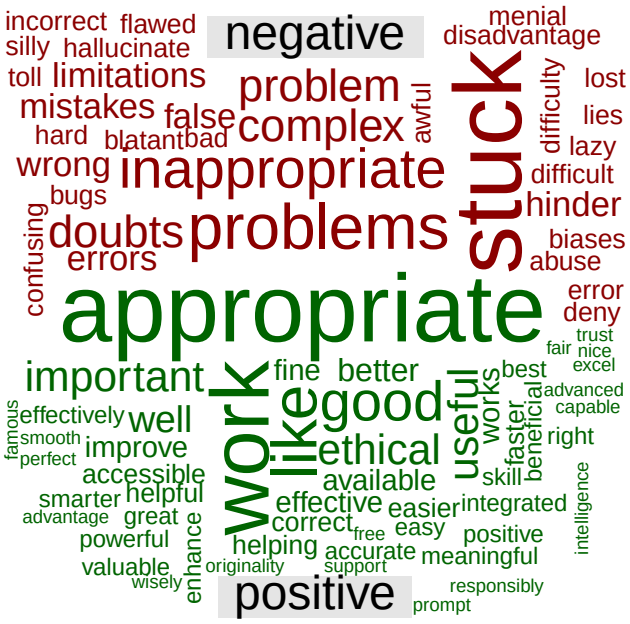


Figure 12: (CHANGE) Boilerplate figure caption

Table 2: Comparing Incidences of Positive and Negative Words.

(a) Top 10 Positive Words

word	n
work	28
appropriate	25
good	15
like	14
useful	11
ethical	8
important	8
well	6
better	5
available	4

(b) Top 10 Negative Words

word	n
stuck	8
problems	5
complex	4
inappropriate	4
doubts	3
problem	3
wrong	3
errors	2
false	2
hinder	2

Table 3: Comparing Incidences of Positive and Negative Words in Student.

(a) Top 10 Positive Words

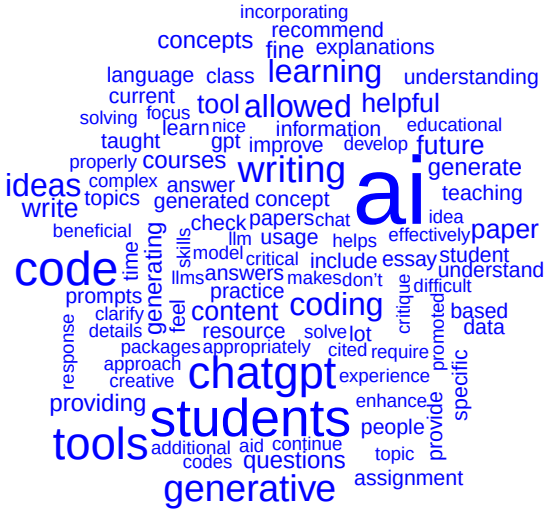
word	n
helpful	9
fine	7
improve	5
recommend	5
beneficial	3
creative	3
effectively	3
enhance	3
nice	3
properly	3

(b) Top 10 Negative Words

word	n
complex	3
critical	3
difficult	3
error	2
errors	2
hard	2
mistakes	2
worry	2
abuse	1
break	1

2.6.2 AI Implementation Recommendations

Figure 13: Word Cloud for Recommendations Comments



3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in Appendix B.

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$y_i|\mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$
$$\mu_i = \alpha + \beta_i + \gamma_i \tag{2}$$
$$\alpha \sim \text{Normal}(0, 2.5) \tag{3}$$
$$\beta \sim \text{Normal}(0, 2.5) \tag{4}$$
$$\gamma \sim \text{Normal}(0, 2.5) \tag{5}$$
$$\sigma \sim \text{Exponential}(1) \tag{6}$$

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular...

We can use maths by including latex between dollar signs, for instance θ.

4 Results

Our results are summarized in **?@tbl-modelresults**.

5 Discussion

5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

5.2 Second discussion point

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In … we implement a posterior predictive check. This shows…

In … we compare the posterior with the prior. This shows…

B.2 Diagnostics

… is a trace plot. It shows… This suggests…

… is a Rhat plot. It shows… This suggests…

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