A Data Science Course Utilizing GenAI

Jonathan W. Browning, John Bustard, Neil Anderson, and Leo Galway
School of Electronics, Electrical Engineering and Computer Science
Queen's University Belfast
Belfast, United Kingdom
{j.browning, j.bustard, n.anderson, l.galway}@qub.ac.uk

***Abstract*—This innovative practice full paper describes an in-depth analysis of the pedagogical implications of incorporating generative artificial intelligence (genAI) tools, specifically ChatGPT, into a data science course for postgraduate masters computing students. This research is grounded in the implementation of ChatGPT in a data analysis course, aiming to evaluate its effectiveness in fostering students' analytical and decision-making capabilities. The study employs a qualitative methodology to assess the educational outcomes of integrating ChatGPT, focusing on its impact on student engagement, learning efficiency, and the development of critical thinking skills in the context of data science. Through a combination of interviews, and analysis of students' project outcomes, we gather insights into the challenges and opportunities presented using genAI in the data science course.**

A notable innovation of our approach is the introduction of a dual-report assessment method, which not only evaluates the students' project results but also their proficiency in prompt engineering — a crucial skill for effective interaction with genAI tools. Our findings suggest that while students demonstrate enhanced data analysis skills, they also face difficulties in accurately framing queries to yield useful results from genAI, highlighting an essential area for further curriculum development. Furthermore, the work delves into the pedagogical strategies that can optimize the benefits of genAI tools in education. It emphasizes the importance of a structured framework that guides students in the ethical use of genAI, encourages critical reflection on AI-generated content, and fosters a deeper understanding of the underlying algorithms and their implications for data science.

The implications of this research extend beyond the classroom, offering valuable insights for instructors, curriculum developers, and policymakers on integrating AI technologies into educational practices. By providing a comprehensive overview of the benefits and challenges associated with the use of ChatGPT in data science education, this paper contributes to the ongoing dialogue on preparing students for a future where genAI might a significant role. In conclusion, this work highlights the potential of genAI to revolutionize data science education by enhancing analytical skills and decision-making capabilities. Continued exploration of effective strategies for integrating AI tools into learning environments, such as data science, is required to ensure that students are equipped with the knowledge and skills necessary to navigate the complexities of genAI for future employment.

***Index Terms*—computer engineering, data science, education, generative artificial intelligence, student experience**

I. Introduction

In our experience as academic instructors, and that of many of our peers, we have found that integrating generative artificial intelligence (genAI) models, such as ChatGPT [1], into higher education presents a unique set of challenges [2], [3]. Similarly, students are often apprehensive about their ability to effectively interact with genAI models, with skepticism about the impact on their future careers [4]. However, the clear potential impact that genAI could have across many industries [5], including data science, is indisputable.

In a typical semester of a data science course, the aim is to build students' confidence in their ability to plan and undertake data analysis, convincing them of the value of these skills, while providing them compelling examples of how this type of work is important to various businesses. Thus, providing real world context and not just theory. However, there was a concern that genAI model usage would make our data science course too simple for students as it could assist with many aspects of their individual project [4]. This a is pressing concern for many instructors, that utilize coursework as part of their assessment methods. It can be expected that students will use genAI or attempt to use it. Therefore, pretending genAI models would not have an impact on our previous course design was not an option.

In response, our data science course has been updated to encourage students to fully engage with genAI models, such as ChatGPT. The approach utilized was guided by two objectives: Firstly, make it easier for students to perform data analysis, especially those with very limited experience of using Python. Secondly, ensure the students understand the goal of their individual project and effectively utilize genAI to assist them. The course was redesigned to incorporate ChatGPT into the course assessment, whilst still adhering to the existing project-based learning approach. The students were provided with a worked example to guide their interactions with ChatGPT.

The main contributions of this work are summarized as follows:

1) This paper presents an approach to incorporating genAI, specifically ChatGPT, into a data science course. This represents a significant shift in pedagogical methods for teaching data science.
2) An evaluation of how the integration of genAI impacts student learning is provided, highlighting both the benefits and challenges encountered.
3) An assessment method through the introduction of a 'prompt engineering report' as part of the course assessment is presented; this unique contribution encourages students to critically evaluate the responses generated by AI models. Sufficient detail has been provided for others, such as the course design and brief sample rubric, to adopt and adapt this model of teaching data science.

4) Discussion of the qualitative results from both the students and instructor running the course, provides insights on the benefits of the updated course design, and also areas for improvement.

II. Background

The integration of genAI into software development and education is a rapidly evolving field, with significant contributions shaping our understanding of its implications. Daun and Brings [6] note that tools like OpenAI's Codex, while reducing manual coding efforts, necessitate a comprehensive understanding of software engineering disciplines such as requirements engineering, design, and testing, where human expertize is crucial. Ahmad et al. [7] expand on this, observing that ChatGPT can generate diverse software artifacts but still requires human oversight for consistency and ethical considerations in software architecture.

In educational settings, the impact of AI is equally profound but complex. Ouh et al. [8] evaluate ChatGPT's efficacy in programming exercises, finding that it excels with clear instructions but struggles with complex tasks, indicating the need for careful integration into curricula. Jacques [9] suggests applying strategies from math education, like problem-solving and critical thinking, to computer education, using AI-generated code as a learning tool. This idea of leveraging AI for educational enhancement is further explored by Finnie-Ansley et al. [10], who demonstrate that Codex often outperforms students in CS2 programming exams, suggesting a shift in educational approaches. Finnie-Ansley et al. also examined Codex's impact on introductory programming education [11]. They demonstrate its adaptability in solving various programming tasks, raising crucial considerations about future programming education in the era of improving genAI technologies.

The potential and challenges of AI in education are further discussed by Kasneci et al. [12]. They provide a balanced view of large language models, highlighting their ability to engage students and personalize learning, while also pointing out risks like bias and over-reliance. This theme of balancing benefits and risks is echoed by Malinka et al. [13] in their assessment of ChatGPT's capability to complete university-level tasks. They advocate for adapting higher education methodologies to harness AI's benefits while mitigating its risks.

Hassani and Silva [14], and Tu et al. [15] delve into the specific domain of data science education. Hassani and Silva highlight ChatGPT's role in automating tasks and aiding decision-making, tempered by concerns over biases and plagiarism. Tu et al. advocate for integrating large language models into data science curricula, emphasizing a paradigm shift in teaching to leverage these tools while nurturing human creativity.

Collectively, these studies underscore the potential of AI in educational settings. They highlight the need to balance AI's opportunities with its challenges, fostering critical thinking, ethical awareness, and adapting teaching methodologies. As the possibilities and limitations of AI in educational contexts are explored, a proactive and nuanced approach becomes essential in preparing for an AI-integrated future in teaching and learning. Notably, a gap remains in the literature regarding the integration of genAI into data science courses using a project-based learning methodology, which this work aims to address, through an initial innovative solution.

A. *Previous Course Design*

This data science course has been running every summer semester for several years for postgraduate students studying a Master of Science (MSc) in software development. The course utilizes a project-based learning approach. Further details of the previous course structure can be found in [16], and what follows now is a brief overview of the previous course design.

The course is conducted entirely online, with a two-hour lecture delivered every week and two two-hour drop-in sessions run online every week to handle student queries. The course aimed to foster and develop professional related skills important to data science, such as resourcefulness, pro-activity, creativity, abstract thinking, critical thinking, and problem-solving. These skills were complemented by domain specific skills, such as data cleaning, data visualizations, reasoning, and communication. At the start of the course the students choose an industry to investigate based on a list of standard industrial classification (SIC) codes, which describe all industries that contribute to the economy.

The course assessment involved the production of a five-chapter report and associated code created to clean and visualize data. Each chapter in the report represented separate stages of work the students completed, including interviewing an expert in the area of the chosen SIC code, surveying existing data sources, planning to analyze a dataset, cleaning a gathered dataset relating to their SIC code, and analyzing using visualizations. This is summarized as a flow diagram in Fig. 1, which has each chapter within the report broken down into key components of work. The students were also given previous exemplar reports to better understand the level of work they had to produce [17].

III. Updated Course Design

In light of the public interest and adoption of genAI at the beginning of 2023, the course has now been updated to better reflect the changing landscape that genAI is bringing to data science. The course still runs during the summer semester for postgraduate students studying a MSc in software development, using the project-based learning approach. The course runs entirely online as before with a two-hour lecture delivered every week and two two-hour drop-in sessions run online every week to handle student queries. Previously, the students had the option to choose any data analysis tool they wished to complete data cleaning and visualizations. Now the students are required to use Python. This was decided as it aligned best with the learning outcomes of the MSc degree program and students predominantly chose Python in the past [16]. This also has the added benefit of allowing teaching

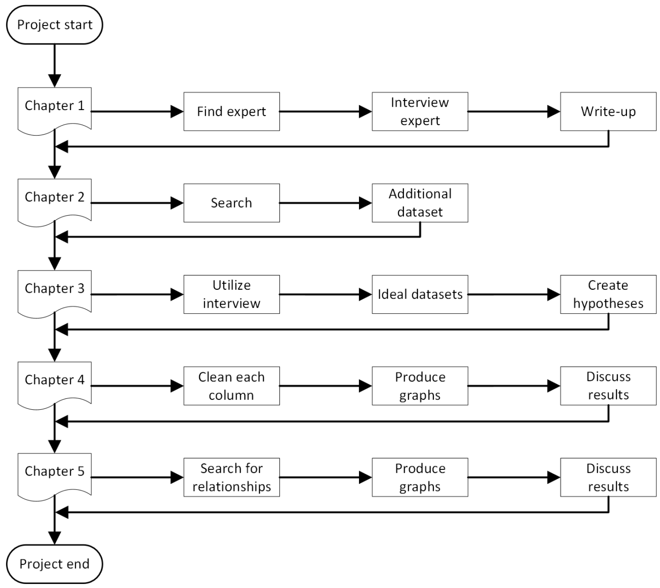

Fig. 1: Flow diagram of the previous course assessment, which is undertaken throughout the duration of the course.

assistants to offer better targeted support and streamlining assessment marking.

A. *GenAI*

It was recognized early in the 2022/23 academic year that genAI could vastly disrupt how the course previously ran. However, given the capabilities demonstrated by genAI, it was decided to actively adopt genAI and mandate its usage within the course. This decision was also taken because of the adoption genAI has received from industry [18]. Therefore, if higher education is preparing students for employment post-graduation [19], students need to be better prepared to face the new and changing landscape. This results in students needing to have experience of using genAI models effectively. It is similar to how the Google search engine previously disrupted education [20]; it can be seen as unavoidable and to avoid it is to actively disadvantage graduates, who would be expected to use it effectively in the future.

It is clear genAI can produce lots of text relatively quickly, yet the user needs to be able to understand what it is producing and evaluate if it is useful for their purpose. This evaluation of what a genAI model produces is highly important. This could be reduced to the discussion of training students to be better prompt engineers. Yet, surely it is more than just prompt engineering when there are multiple components that fit together within a project. The higher skills of design, understanding requirements, critical evaluation/analysis, and perspective of the bigger picture need to be developed.

B. *Assessment*

As part of the course assessment, students must create two reports. The first report is similar to that of the report students created in previous iterations of the course, as detailed in Section II-A. However, the new second report is a prompt engineering report. It is designed so the students demonstrate they had tried different prompts to get valuable information from ChatGPT or any other genAI model. The prompt engineering report is directed so that students document the prompt used and then the advantages and disadvantages of the genAI's response. The actual genAI responses would be contained in the appendix of the report. This is because so much text is generated it is very difficult to understand the flow of prompt engineering when all the response text is included. This is not an ideal format and hopefully, new tools will emerge that help support and document prompt engineering, as this compromise is not ideal and does slow the process quite a bit.

Both of these reports are colour-coded within each chapter and section to indicate where the content came from: expert opinion/accounts of events, genAI response to prompts, or personal reflection. This is required to help demonstrate the critical thinking the student used and how they synthesized all of the information available to them from their chosen expert and genAI model. All Python code used within chapters four and five of the first report must be submitted as well. Each report will have five chapters. However, iterating over each, when possible, is desired. For example, for chapter 1, it would be useful to gain initial insights from ChatGPT first, before going to interview the expert. Furthermore, it might be helpful to feed the interview results back into ChatGPT to see if there is anything underlying that can be understood, that might have been missed. This back and fore procedure between the two reports is believed to produce the best results as it allows for further refinement and reflection within each chapter.

For the purposes of marking the two reports, which make up the project assessment a rubric has been created. Each chapter is weighted equally and the corresponding chapter from each report are assessed together for cohesion. For demonstrative purposes and to give insight into how other instructors might replicate this course design, a small sample (i.e., reduced number of descriptive comments) of the rubric for chapters one and two is provided in Table I. In this rubric an equivalent proficiency scale is used, which corresponds to the institutions equivalent scale. For each chapter a minimum of five comments are chosen to reflect the students work. Based on the proficiency scale there is an associated mark and the average mark is found for each chapter based on the reflective comments. The comments for all the chapters are returned to students as summative feedback. This method allows for more consistent and time efficient marking, whilst being able to provide individual feedback to all students in the cohort.

C. *Worked Example*

Considering that students were previously provided with exemplar works, but now those did not exist, it was decided to create a worked example. This served two purposes. Firstly, it provided an opportunity to complete the project from the perspective of a student, giving us a better insight to understand what difficulties might arise for the students. Secondly, the

TABLE I: Sample rubric for chapters one and two in the reports for the updated course design.

Chapter	Proficiency Scale	Comment
1	Excellent	Exceptional business process modelling/task table/values.
	Excellent	Very strong insight into values, causal factors and unquestioned assumptions, and creativity shown.
	Very good	Very good conclusions.
	Very good	Very good project walk-through, captures issues, successes and causes.
	Good	Reasonable introduction on project, captures some issues and opportunities, no commentary.
	Good	Roles and tasks from expert and AI with no commentary and no review by expert.
	Satisfactory	Some interesting prompt engineering approaches like the rating of the response.
	Satisfactory	Reasonable conclusions more focus on how data analysis could be applied would be valuable.
2	Excellent	Very insightful values.
	Excellent	Outstanding space of work section.
	Very good	Very good lenses section.
	Very good	Very good conclusions.
	Good	Good values that have original ideas.
	Good	Good space of work section and a focus on helping others continue the work.
	Satisfactory	Okay conclusions but doesn't talk about analysis.
	Satisfactory	Satisfactory values but minimal.

students will not have been tasked with actively using genAI to assist them in this manner before. Therefore, there was no template or format as a starting point and creating the worked example allowed refinement of the formatting.

The students were provided with a worked example (i.e., both reports) for one SIC industry, which was software development. The reports were not a complete version but the second report (i.e., the prompt engineering report) shows lots of examples of how to prompt ChatGPT in different ways. For example, it shows how to tell ChatGPT to be an expert on a certain topic, how to use in context learning by giving it real examples, and how to create structured outputs, such as tables. It also includes getting ChatGPT to create a graph of possible causal relationships using the dot file format [21], so that they could be visualized easily. The students should seek out further information that might be useful to provide a fuller context for the operation of businesses in their chosen industry. Hence, they can explore other roles besides their chosen expert, by using ChatGPT. In the prompt engineering report the following was given as an example of how to prompt ChatGPT to produce useful information about the tasks a project manager within a software development company performs:

`Construct a table summarizing the main tasks that a project manager performs on a typical government contract project. Please provide the data in the following format:`

`Role, Situation, Action, Expected Outcome, Duration, Frequency.`

`Software Developer, Shown ticket by business analyst, Give feedback to make the ticket definition unambiguous, Ticket is closer to being able to be scheduled in a sprint 30 mins, 4 per sprint.`

The information about a government contract project was included, as in this example after interviewing the expert, who was a software developer, it was found that a high proportion of the software development company's work is from government contract projects. However, the example shows how ChatGPT could be prompted to give information about roles that are adjacent to the interviewed expert to provide more insights. The response from the prompt is given in Table II. This table is included in the project report, whilst the critical analysis of the prompt and the response is given as follows in the prompt engineering report:

`Advantages: the table format is a very efficient way to get a lot of detail in a single response.`

`Disadvantages: some of the durations seem completely implausible. For example, suggesting that a project manager could identify the project scope and objectives in a 2 hour meeting with a client. From information from the expert it appears that creating some kind of detailed plan is a necessary part of the bid process and would then be followed by even more detailed requirements gathering before the project started. The impression from the expert was that there was quite a large amount of upfront, waterfall style project planning.`

A key factor in creating this worked example was ensuring that the prompts were carefully worded to ensure they described how students would be assessed on the quality of their response. These prompts were not necessarily good examples of prompt engineering. However, as students were studying these prompts it was important that the text guided them to the goal of their work rather than just showing them types of questions they could ask. With ChatGPT being such a powerful technology, with the ability to generate very large amounts of text, focusing on what is important and clearly communicating that to students becomes even more important. The students also need to demonstrate this important skill.

IV. Research Question

In detail, we address the following research question (RQ):

RQ: Has updating the course design to include genAI been effective?

TABLE II: ChatGPT example response.

Role	Situation	Action	Expected Outcome	Duration	Frequency
Project Manager	At the beginning of the project	Meet with stakeholders and gather project requirements	Clear project scope and objectives are defined	2 hours	Once at project start
Project Manager	Beginning of each sprint	Organize sprint planning meeting	Tasks for the upcoming sprint are defined and assigned	2 hours	Each sprint
Project Manager	During the sprint	Monitor the progress of tasks and address any issues or blockers	Tasks are completed on time, and any issues are resolved quickly	1 hour/day	Daily
Project Manager	In case of changes to project scope, deliverables, or timelines	Conduct change control processes and adjust project plans accordingly	Changes are managed effectively and project plans are updated accordingly	2-4 hours	As needed
Project Manager	At the end of each sprint	Facilitate sprint review and retrospective meetings	Successes and areas for improvement are identified for the next sprint	2 hours	Each sprint
Project Manager	Regular intervals throughout the project	Communicate with stakeholders to update them on project status and issues	Stakeholders are informed and any concerns or questions are addressed	1 hour	Weekly
Project Manager	When risks or issues are identified that could impact project delivery	Develop and implement risk mitigation strategies	Risks are managed effectively and their impact on the project is minimized	2 hours	As needed
Project Manager	At the end of the project	Facilitate project closure activities, including final project review	Project is successfully closed, and lessons learned are documented	4 hours	Once at project end

V. Method

To address our research question, a qualitative methodology is utilized by gathering student comments throughout the duration of the course, which they provided during the drop-in sessions or in the online learning environment. Anecdotal evidence provided from the instructor leading the course is also included.

VI. Results

The results for the academic year 2022/23 is provided in this Section. This is the first time the updated version of the course was run. The total number of students enrolled on the course was 56.

A. Student Feedback

What follows is brief commentary provided by students in regards to their experience of the updated course design:

"The industry expert interview was interesting, preparing for it, and converting it into the report gave good insight into how a data analyst would go about industry research. Establishing issues and values was a good process for getting into the mind frame of an analyst."

"I really enjoyed interviewing my expert, and felt that they were able to give interesting and useful insights. ChatGPT was useful for filling the gaps for more general sections that I didn't have time to focus on."

"I struggled with writing a plan for conducting data analysis but the worked example helped me to understand what to look for in a plan, using ChatGPT to make a plan and look closer at given sections, helped."

From their comments it is evident that some students did find value in using ChatGPT to assist them in their project. However, it is also clear that some students still find the fundamental aspects of an open-ended data science project difficult to grasp:

"Having good insights into data analysis and how it works is crucial for doing the project properly and I think a lot of students, including me, lack these skills and mindset."

This could be due to the students' inexperience of open-ended individual projects. Up until this course, these students would not have been tasked with such a project before. Therefore, the students might find this level of problem-solving to be very challenging, compared to their previous experience in the Master's degree.

B. Instructor Experience

1) Adoption of GenAI: Fundamentally, the adoption of genAI was empowering, resulting in the course focusing more on why analysis was being performed rather than how to perform it. This is somewhat double edged as it is much harder to teach students to think in a rational and data driven way, than it is to get them to memorize API syntax. Some students, that lack a background or experience in this way of thinking, find it very difficult to learn. This is valuable as it is the most important factor in a student's ultimate success in data science. What is clear is that more time needs to be spent getting students to think in rational data driven ways.

This is challenging within a single course, with the amount of practical work required to cover each of the key steps of data analysis.

It was noticed that ChatGPT has a good understanding of the data analysis process and proposes sensible high level plans for approaching analysis problems. The browser plugin for ChatGPT was extremely useful for finding public datasets that could be analyzed. This meant work that would have taken students weeks to complete in the previous version of the course, could be replaced with a single prompt. The ChatGPT code interpreter enabled much more sophisticated analysis to be performed than previous in years. For example, students were shown how to create a random forest model to predict one column and then perform sensitivity analysis to numerically rate the importance of other columns in predicting this value. This provided a new insight into the relative importance of different features and classification values.

2) Student difficulties: It was found that students tend to interact conversationally with ChatGPT as a chat bot and receive generic responses, which is not helpful to their project. Or conversely, students try to get ChatGPT to do everything in one prompt. For example, prompting ChatGPT to create a table with all the steps for a plan to analyze a dataset. The resulting report content discussing how the visualizations would be useful is very generic and does not explicitly explain how the visualizations could be used. Furthermore, some students did not realize they can split a task into a high level plan and then ask for more detail on each step. Overall, this shows the students naivety in interacting with genAI models, such as ChatGPT, to contribute to a large project.

As mentioned previously, a key skill being developed is critical analysis/evaluation in order to synthesise text generated by AI models, along with information gained from interviewing a person. Some students found it difficult to use both genAI and human judgement together, and did not realize the goal is to create the best report possible not an "AI version" and a "human version". Another pitfall is that students accept any response the genAI model gives them based on their first prompt, and they are not evaluating their prompts and associated responses to get better results. This demonstrates a lack of experience with prompt engineering.

Often the students didn't realize that most of their problems can be solved by prompting ChatGPT. For example, if students ask ChatGPT about data sources relevant to their industry, they get back a large list of sources they need to pay for, then they did not know what to do. Instead of simply asking for public data sources. This shows a lack of initiative that is required when working on a project that does not have a binary answer. Some students can be swayed by very generic sentences that lack concrete meaning or substance. For example,

```
This graph will help us visualize the
financial landscape of the legal industry
and understand the growth of individual
firms.
```

At first glance appears something useful is being done but it is not concrete enough to identify what kind of results might be shown and what conclusions to draw from it. This shows that ChatGPT can write in a professional, low information, style and students don't realize how vacuous it is. After all, the goal of their project is not quantity over quality.

Much of these problems are from a lack of experience using genAI, which hopefully will change as more courses incorporate it in the future. Overall, this would suggest there is a need for explicit training in using genAI models. Or improving the course to briefly cover more on prompt engineering and a mechanism for course instructors to detect when the students are not utilizing genAI proficiently.

A common problem from the previous years that remains is a student's tendency to focus on very narrow data sources, i.e., specific to a country, or specific to all the specialty details of the industry they are analyzing. This results in them not learning from the more general industry they are apart of, e.g., focusing on UK sales of ski apparel, rather than using data from seasonal sporting goods equipment in general or seasonal clothing in general to find more data and other sources of insights in what makes such businesses successful. The worked example including the prompts given to the students was meant to act as a starting point, but the students didn't experiment or try alternatives. This was a drawback as they seemed to heavily rely on it to produce their own work instead of using it as intended.

Overall, students from the updated course design produced a lot more work with the assistance of genAI. The genAI reduced the need for technical support from teaching assistants, which was an added benefit. In general the content produced by genAI was above average compared to previous years work produced solely by students and in some cases was better than a student has ever produced. However, it was noticed that the best students iterated with the genAI to achieve good results. Students might not have done this to save time, as they also have other demands and modules, therefore not taking the time to reflect and critically analyse their work.

VII. Discussion

This work was aimed at assessing the impact of incorporating genAI, specifically ChatGPT, into a data science course for master's software development students. The evaluation was centered on determining whether the integration facilitated an enhancement in the students' data analytical skills and their proficiency in prompt engineering. Based on qualitative analysis drawn from student feedback and instructor reflections, several key findings emerge.

The integration of ChatGPT into the data science curriculum has proven to be generally effective. Students reported enhanced abilities to perform data analysis, citing the genAI's assistance in filling knowledge gaps and providing a scaffolded learning experience. Furthermore, the dual-report assessment method revealed improved student engagement with both the analytical aspects of their projects and the technical skills necessary for effective genAI interaction. These outcomes suggest that the course updates have positively influenced the students' ability to apply data science concepts in practical scenarios.

Despite the positive feedback on genAI integration, students encountered significant challenges in prompt engineering. The results indicate a gap in students' abilities to craft effective queries that yield useful responses from ChatGPT. This gap highlights a critical area for curriculum enhancement, suggesting that future iterations of the course should include more focused training on developing this essential skill. Effective prompt engineering is crucial for maximizing the potential of genAI tools in educational settings.

The findings from this study have several implications for pedagogical practice in data science education. First, there is a need to better prepare students for the cognitive demands of working with genAI tools through targeted instructional strategies that emphasize prompt engineering and critical evaluation of AI-generated content. Second, this work underscores the importance of continuous adaptation in curriculum design to keep pace with technological advancements, ensuring that students remain competitive in a rapidly evolving job market.

The integration of ChatGPT into the data science course has met its primary objectives by enhancing students' analytical capabilities and introducing them to essential genAI interactions. However, the challenges noted in prompt engineering underscore the need for ongoing adjustments to the curriculum. These adjustments should aim to deepen students' understanding of genAI mechanisms and improve their skills in leveraging these tools effectively.

VIII. Conclusion

The integration of genAI, specifically ChatGPT, into the data science course has proven to be a transformative step. It has enabled opportunities for students to foster critical thinking and data-driven decision-making skills. Despite the challenges encountered, such as the need for effective prompt engineering and the evaluation of AI-generated responses, the overall impact has been positive. This experience underscores the potential of genAI as a useful tool in data science education, capable of preparing students for the evolving demands of industry. As instructors continue to navigate this new landscape, our focus remains on equipping students with the skills and knowledge they need to succeed in a increasingly automated and data-driven environment.

References

[1] OpenAI. (2023) Introducing ChatGPT. OpenAI. [Online]. Available: https://openai.com/blog/chatgpt

[2] J. Su and W. Yang, "Unlocking the power of ChatGPT: A framework for applying generative AI in education," *ECNU Review of Education*, vol. 0, p. 0, Apr. 2023.

[3] P. Denny, J. Prather, B. A. Becker, J. Finnie-Ansley, A. Hellas, J. Leinonen, A. Luxton-Reilly, B. N. Reeves, E. A. Santos, and S. Sarsa, "Computing education in the era of generative AI," *Commun. ACM*, vol. 67, no. 2, p. 56–67, jan 2024.

[4] C. K. Y. Chan and W. Hu, "Students' voices on generative AI: perceptions, benefits, and challenges in higher education," *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 43, Jul. 2023.

[5] A. Zarifhonarvar, "Economics of ChatGPT: A labor market view on the occupational impact of artificial intelligence," Rochester, NY, Feb. 2023.

[6] M. Daun and J. Brings, "How ChatGPT will change software engineering education," in *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1*, ser. ITiCSE 2023. New York, NY, USA: Association for Computing Machinery, Jun. 2023, pp. 110–116.

[7] A. Ahmad, M. Waseem, P. Liang, M. Fahmideh, M. S. Aktar, and T. Mikkonen, "Towards human-bot collaborative software architecting with chatgpt," in *Proceedings of the 27th International Conference on Evaluation and Assessment in Software Engineering*, ser. EASE '23. New York, NY, USA: Association for Computing Machinery, Jun. 2023, pp. 279–285.

[8] E. L. Ouh, B. K. S. Gan, K. Jin Shim, and S. Wlodkowski, "ChatGPT, can you generate solutions for my coding exercises? an evaluation on its effectiveness in an undergraduate java programming course." in *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1*, ser. ITiCSE 2023. New York, NY, USA: Association for Computing Machinery, Jun. 2023, pp. 54–60.

[9] L. Jacques, "Teaching cs-101 at the dawn of ChatGPT," *ACM Inroads*, vol. 14, no. 2, pp. 40–46, May 2023.

[10] J. Finnie-Ansley, P. Denny, A. Luxton-Reilly, E. A. Santos, J. Prather, and B. A. Becker, "My AI Wants to Know if This Will Be on the Exam: Testing OpenAI's Codex on CS2 Programming Exercises," in *Proceedings of the 25th Australasian Computing Education Conference*, ser. ACE '23. New York, NY, USA: ACM, Jan. 2023, pp. 97–104.

[11] J. Finnie-Ansley, P. Denny, B. A. Becker, A. Luxton-Reilly, and J. Prather, "The robots are coming: Exploring the implications of OpenAI Codex on introductory programming," in *Proceedings of the 24th Australasian Computing Education Conference*, ser. ACE '22. New York, NY, USA: ACM, Feb. 2022, pp. 10–19.

[12] E. Kasneci, K. Sessler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier, S. Krusche, G. Kutyniok, T. Michaeli, C. Nerdel, J. Pfeffer, O. Poquet, M. Sailer, A. Schmidt, T. Seidel, M. Stadler, J. Weller, J. Kuhn, and G. Kasneci, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, Apr. 2023.

[13] K. Malinka, M. Peresíni, A. Firc, O. Hujnák, and F. Janus, "On the educational impact of ChatGPT: Is artificial intelligence ready to obtain a university degree?" in *Proceedings of the 2023 Conference on Innovation and Technology in Computer Science Education V. 1*, ser. ITiCSE 2023. New York, NY, USA: ACM, Jun. 2023, pp. 47–53.

[14] H. Hassani and E. S. Silva, "The role of ChatGPT in data science: How AI-assisted conversational interfaces are revolutionizing the field," *Big Data and Cognitive Computing*, vol. 7, no. 2, p. 62, Jun. 2023.

[15] X. Tu, J. Zou, W. Su, and L. Zhang, "What should data science education do with large language models?" *Harvard Data Science Review*, vol. 6, no. 1, Jan. 2024.

[16] J. W. Browning and J. Bustard, "Data science course design for a large-scale cohort using individual project-based learning," in *Proceedings of 7th Conference on Computing Education Practice*, ser. CEP '23. New York, NY, USA: Association for Computing Machinery, Jan. 2023, pp. 17–20.

[17] G. D. Hendry, P. White, and C. Herbert, "Providing exemplar-based 'feedforward' before an assessment: The role of teacher explanation," *Active Learning in Higher Education*, vol. 17, no. 2, pp. 99–109, Jul. 2016.

[18] C. Ebert and P. Louridas, "Generative AI for software practitioners," *IEEE Software*, vol. 40, no. 4, pp. 30–38, Jul. 2023.

[19] J. Brennan, "Preparing students for employment," *Studies in Higher Education*, vol. 10, no. 2, pp. 151–162, Jan. 1985.

[20] D. Loertscher, "The digital school library: a world-wide development and a fascinating challenge," *Teacher Librarian*, vol. 30, no. 5, pp. 14–25, Jun. 2003, publisher: E L Kurdyla Publishing LLC.

[21] Dreampuf. (2023) GraphVizOnline. GraphViz. [Online]. Available: https://dreampuf.github.io/GraphvizOnline/