BRIDGING THE GAP: TEACHING DATA ANALYTICS TO BUSINESS STUDENTS USING R

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Business curricula are increasingly offering data analytics courses. However, training business students in data-analytic thinking and exposing them to new software requires balancing technical skills with domain-specific knowledge in ways that keep students motivated. In-class observations, student evaluations, and student reflections were used to develop and iteratively improve a data analytics course that overcomes these challenges. A survey and retrospective interviews supplemented these to formulate the lessons learned presented in this paper. These include using the software R as a Blackbox application and creating an atmosphere of collaborative learning. The use of relevant datasets and examples also appealed to students' intrinsic motivation for their subject.

Keywords:
data analytics,
situated learning,
domain experts,
business education,
analytic thinking

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1 Introduction

Organizations are successfully leveraging the benefits of big data analytics to develop better products and services, reduce costs, mitigate supply chain risks, increase productivity, and gain a competitive advantage (Kokkinou et al., 2023). The resulting focus on data-driven decision-making has increased demand not only for expert data analysts (U.S. News & World Report, 2024), but also for business professionals equipped with skills in data science and analytics (Gharehgozli et al., 2024; King, 2022). In larger organizations, training in such skills is essential because data analysts and business professionals must collaborate to define relevant business problems or questions (Provost & Fawcett, 2013; Vance et al., 2022). Ideally, both parties should possess a solid understanding of each other's domain to enable meaningful dialogue and informed decision-making (Provost & Fawcett, 2013). In Small and Medium Enterprises (SMEs) lacking dedicated data analytics resources, such training is necessary, as business professionals must independently engage in data-driven decision-making without support from data scientists or analysts.

In response to the scarcity of data analytics expertise, organizations are increasingly turning to trainees and recent graduates (Janssen, 2022; Kokkinou, 2023). This trend highlights the need to develop data analytics courses and programs tailored to business management students that familiarize them with data analytic thinking and expose them to software suitable for processing large data sets (Birt et al. 2023; Gharehgozli et al. 2024; King 2022). However, training business students in data analytics presents challenges (Msweli et al., 2023). Business majors often lack the prerequisite knowledge of statistics and computer programming required by many existing data analytics classes (King, 2022; Wang and Gu, 2018).

Despite extensive attention to best practices in developing data analytics courses and curricula for technical students, limited guidance exists for designing courses specifically for business students (Pan and Mazzei, 2023), particularly regarding software integration (Birt et al., 2023). The present study, therefore, describes how this challenge was tackled in the development of two data analytics courses targeted at (a) finance and (b) supply chain majors at two universities of applied sciences. Both courses were iteratively improved based on feedback from students, colleagues, and industry practitioners over five academic years.

In the subsequent sections, a brief theoretical background is provided on data analytics and on other courses requiring programming. Subsequently, the course design is described, including the choice of software, course and project assessment, and the selection of instructional materials. Lessons learned that can help instructors develop similar courses are presented, followed by the conclusion.

2 Theoretical Foundations

Universities are increasingly offering data analytics and data science courses in response to both industry and student demands (Gharehgozli et al., 2024). Such courses are intended to develop students' data analytic thinking and data acumen. Given that data analytics and data science are multidisciplinary, it is not surprising that these courses have been offered by university departments as diverse as business schools (Wang and Gu, 2018) and statistics departments (Hicks and Irizarry, 2018), with little consensus on where such courses belong. This is further complicated by the fact that, as in the academic and professional contexts, the fields of data analytics and data science courses overlap considerably (King, 2022). Areas of overlap include (1) data mining algorithms, (2) data visualization and storytelling, and (3) the integration of computing into the course, in particular R and Python (Hicks and Irizarry, 2018; King, 2022; Msweli et al., 2023).

A significant concern when integrating computing into a course for students without a computer programming background is that learning to program for the first time can be challenging for many (Echeverría et al., 2017; Msweli et al., 2023). Several educational theories and corresponding pedagogical approaches contribute to our understanding of how to keep students motivated through this relatively steep initial learning curve. From a social constructivist perspective, learning is viewed as a primarily social activity, and pedagogical approaches should therefore emphasize students' engagement with others (Barak, 2017). The situated learning perspective further stipulates that learning takes place within authentic activities (Vargas et al. 2024). Hicks and Irizarry (2018) similarly challenge traditional statistics courses for focusing on mathematics rather than on using data to solve real-world problems or answer questions. To bridge this gap, they propose several teaching principles emphasizing the use of examples, such as building the course around case studies, structuring course activities to mimic a data analyst's experience, and demonstrating the importance of critical thinking through relevant examples.

To help students make the connection between the software and the rationale for teaching it, R is frequently taught alongside statistics (Tucker et al., 2022) or data analytics courses (Hicks and Irizarry, 2018; Wang and Gu, 2018). Some instructors prefer to have students type all commands and datasets by hand, and only later move to using scripts. Other instructors prefer that students start their learning with preexisting scripts. Most emphasize the importance of providing extensive support to students to prevent them from becoming frustrated or discouraged (Hicks and Irizarry, 2018; Tucker et al., 2022). Despite the prevalence of best practices in (1) teaching data analytics and (2) teaching statistical software, there is a lack of guidance on teaching data analytics in conjunction with statistical software to non-experts.

3 Course Design

In this section, we describe how the aforementioned educational theories and pedagogical approaches were used to design and iteratively improve two data analytics course(s), (a) for 4th year Bachelor of Science in Finance & Control (BsF&C) and (b) one-year Master of Supply Chain Management (MsSCM) students at two Dutch Universities of Applied Sciences. For each course, we first describe its scope and motivation and how it fits within the curriculum. In the Dutch educational system, the BsF&C is a four-year program comprising 240 European Transfer Credits (ECTs). While this program had been running since 2011, the data analytics course was introduced as part of an extensive curriculum redevelopment in 2020 in response to a quickly changing profession, requiring auditors, accountants, consultants, and other professionals to evolve their skill sets (Deloitte, 2020). Students entering the course are expected to have completed a basic statistics course in their first year, amongst other coursework. The course is worth 8 ECTs (in the European Credit Transfer system, 1 ECT is equivalent to a study load of 27 hours). It spans 10 weeks and is assessed through an individual project. The MsSCM program was developed in response to industry requests for supply chain specialists who can recognize and implement innovations in their field and act at a strategic level. Students entering the course are expected to possess prior knowledge of logistics and supply chain management, statistics, accounting, finance, and operations management. Both courses (one within BsF&C and one within MsSCM) focus on students mastering data analytics procedures and on acquainting them with the broader context of data analytics. We describe the course design for the two courses here. We first clarify the choice to use the software R, as it has implications for course design. We subsequently discuss the assessment, the topics covered, and the instruction materials. As both courses have undergone multiple Plan-Do-Check-Act iterations at their respective institutions, the main changes and the motivations will be explained.

3.1. Choice of Software R

A deliberate choice was made to use the R software with RStudio. Software such as R and Python offers several advantages over tools like Excel Solver, including greater versatility and the ability to handle complex analyses. Whereas Python is a general-purpose programming language, R is an open-source software environment for statistical computing and graphics ("The R Project for Statistical Computing," 2021). Both R and Python have rich ecosystems of libraries (Python) and packages (R) built around a range of modern statistical methods, making them highly versatile and dynamic (Firth et al., 2021). Although R is perceived as having a steeper learning curve, RStudio, an integrated development environment for R, helps make R more accessible. It offers a console and an editor that support direct code execution, making it much easier to write and edit scripts ("RStudio," 2021). The tools for debugging and workspace management also make it easier for users with little coding experience.

While training students to use software such as Python and R required significant time and effort, it was considered preferable for several reasons. First, doing so would expose students to new software, equipping them with transferable skills (Sankaran et al., 2023). Second, it would introduce students to the basics of programming. Third, many videos and tutorials were available for students interested in improving their knowledge of Python or R beyond the course objectives (Firth et al., 2021). Fourth, because Python and R are open-source, students interested in implementing these tools at their place of employment can do so without needing budget approval. The final decision to use R instead of Python was made based on two additional, context-specific reasons. First, the lecturers had more experience with R and thus were better equipped to help students who encountered bugs. Second, the MsSCM students also needed to learn new software for their research methods course, and R was a better fit than Python because of its explicit orientation toward statistics (Sankaran et al., 2023). The decision to use R instead of Excel Solver or Python was revisited several times, as students perceived learning R as a driver of workload. Course evaluations showed that despite R being challenging, students felt a sense of achievement and saw R as valuable after completing the course.

3.2. Course Project & Assessment

Consistent with the principles of situated learning (Vargas et al., 2024), students in both courses were assessed individually through a project that mimicked how data analytics teams solve real-world problems. In line with the principles of collaborative learning (Barak, 2017), students were permitted to collaborate on specific tasks, such as data preparation, and to support one another in overcoming challenges, such as debugging. However, despite working with the same dataset, each student was required to work independently. This included formulating their own business objective and corresponding data mining objective. Students also had to conduct their own modeling and evaluate their models. They could choose their own path by focusing on different target variables or by using distinct subsets of the data.

In the first year of the BsF&C course, student groups were allowed to select their own dataset. However, this frequently caused problems with (a) students who were trying to find a dataset that would be "easy" to analyze, and (b) students who were insecure and trying to make sure they found the best possible dataset. In the subsequent two years, lecturers cooperated with Tony's Chocolonely, a rapidly growing chocolate-producing social enterprise. This gave students a real-life case and a corresponding dataset. An important advantage was that all students received the dataset at the outset of the project. The brand was familiar to most students and appealing because of its focus on social sustainability. However, the dataset primarily focused on marketing and sales, and the students indicated they did not find it intrinsically motivating. Furthermore, students reported spending extensive time preparing the data, and that it was too large for their computers to handle. In hindsight, the dataset was too large for most students to handle and not relevant to their experience. In subsequent years, an in-between solution was chosen: a real-life dataset that better fit the students' domain expertise was "prepped" by the lecturers to make it more manageable for the students. A logistics-themed dataset from the second-hand clothing company Vinted was used. Similarly, the brand was familiar to students, thereby increasing their intrinsic motivation. Unlike in prior years, the lecturers conducted some data preparation in advance. This reduced students' workload without affecting learning outcomes. Preparing the data for the students improved their intrinsic motivation to work on a real-life case, increased their self-efficacy, and reduced their frustration.

The project was assessed through an individual portfolio comprising a consulting report and a methods report. In the consulting report, students identified key business decisions and related metrics. They also summarized the analysis process and presented their key findings and recommendations. Their consulting reports also needed to include appropriate visualization. In a separate methods report, students detailed their analysis using Cross-Industry Standard Process for Data Mining (CRISP-DM), a broadly recognized framework (Data Science Process Alliance, 20-23; Wirth and Hipp, 2000). Initially, the MsSCM students submitted multiple separate assignments intended to test their knowledge of various data mining techniques. However, in the fall of 2024, the multiple assessments were replaced by a single portfolio to reduce students' perceived workload.

3.3 Instruction, Book & Other Materials

Both courses consisted of weekly teacher-led sessions and workshops. The weekly teacher-led sessions were used to present theoretical concepts and to link them to students' future professions through examples. The CRISP-DM framework was introduced to the students during the first week and was frequently used to structure projects and illustrate how data analytics could be linked to business problems. The business understanding and deployment steps were particularly relevant to the course objectives, as they bridged the gap between domain and technical expertise. Domain-specific examples (e.g., supplier selection and procurement) were used to illustrate this process. In subsequent weeks, students were gradually introduced to various statistical concepts, starting with descriptive statistics and regression, and then moving on to supervised and unsupervised data mining techniques. The instructor-led sessions focused on explaining theoretical concepts, illustrating them with domain-specific examples, and providing demonstrations. Students also had ample time to ask questions. The work sessions were self-led. The instructor began each session by explaining the purpose of the activities and addressing any questions. Students were provided with annotated R scripts corresponding to exercises in the prescribed book. The instructors reviewed the book publisher scripts and annotated them to provide additional examples and explanations. As the course progressed, students had to fill in an increasing number of commands themselves.

As business analytics typically requires teams of experts from separate fields to work together, cooperation was integral to the course design (Vance et al., 2022). During the work sessions, students worked in groups of three. They were encouraged to solve problems together, but instructors were available to answer questions. In week 5, students were introduced to the project, and progressively more class time was allocated for them to work together and ask questions about it. Thus, students encountering problems could seek help and avoid getting discouraged. The book prescribed for the course was "Business Analytics" by Jaggia et al. (2020). This book was selected for its clarity of explanation, extensive examples of R-based analysis, and the provision of R scripts.

4 Methods

To assess the course design and student achievement, multiple methods were employed. Both universities of applied sciences have established PDCA processes at the course and program levels. For both courses, student roundtables were organized halfway through and at the end, supplemented by formal, anonymous written evaluations. Furthermore, both study programs have an industry advisory board, with industry professionals serving as external advisors. For example, at its June 2024 meeting, the MsSCM industry advisory board reviewed the scope, content, and relevance of the data analytics course. Discussion points included the choice to use R, the importance of discussing ethics, legislation, and data governance, and examples of data analytics applications. In addition to formal PDCA activities, students were asked to share their reflection reports (BsF&C) and/or participate in reflective interviews (MsSCM) at the end of the course, and at the end of their study program, resulting in a volunteer sample. The authors analyzed the anonymized roundtable discussion notes, course evaluation comments, industry advisory meeting notes, reflections, and interview transcripts. The full overview is shown in Table 1. It is important to note that the authors were also the lecturers of record, introducing the possibility of bias. Pedagogical advisors of the respective programs were therefore asked to review the data and independently verify the analysis and conclusions. This entailed, among other things, ensuring that all results received equal attention and that no social desirability bias was introduced through selective data collection and interpretation. For all research activities, informed consent was obtained from all participating students. As all materials used were anonymized, ethics committee approval was waived by both institutions.

Table 1: Overview of information per cohort per study program

Cohort	BsF&C	MsSCM
Fall 2020	1st iteration, course designed by 1st and 2nd author. Course given online. Student feedback obtained during course execution through student roundtables, student written evaluation at the end of course, student roundtable at the end of the course (all organized by semester coordinator). Lecturer observation and reflections.	Course not offered.
Spring 2020	Course not offered.	1st iteration, authors not involved
Fall 2021	2nd iteration Course given in person by 3rd author and one colleague. Student feedback obtained through student written evaluation at the end of course, student roundtable at the end of the course (all organized by semester coordinator). Lecturer observation and reflections.	2nd iteration, course extensively revised by 1st author. Course given by 1st author in person. Course given in person, with the exception of the last two weeks. Student feedback obtained during course execution through student roundtables, student written evaluation at the end of course, student roundtable at the end of the course (all organized by program coordinator). Lecturer observation and reflections. (n =21)
Fall 2022	3rd iteration Course given in person by 3rd author and one colleague. Student feedback obtained through student written evaluation at the end of course, student roundtable at the end of the course (all organized by semester coordinator). Lecturer observation and reflections.	3rd iteration. Course given in person by the 1st author. Student feedback obtained during course execution through student roundtables, student written evaluation at the end of course, student roundtable at the end of the course (all organized by program coordinator). Lecturer observation and reflections. (n =28)
Fall 2023	4th iteration Course given in person by 3rd author and one colleague. Student feedback obtained through student written evaluation at the end of course, student roundtable at the end of the course (all organized by semester coordinator). Lecturer observation and reflections.	4th iteration Course given in person by the 1st author. Student feedback obtained during course execution through student roundtables, student written evaluation at the end of course, student roundtable at the end of the course (all organized by programme coordinator). Lecturer observation and reflections. (n =32)
Fall 2024	No change	No change

Source: Authors' Own Work

To examine the course's impact on data analytic thinking, data were collected in 2024 via a census approach to compare students' ratings of their data analytic thinking skills before and after the course (see Figure 3). For this purpose, an existing four-item scale of organizational data analytic capability was adapted to the individual learner context (Srinivasan and Swink, 2018). Sample items included "I easily combine and integrate information from many data sources to use in my decision making" and "I use advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making," anchored with 1 (completely disagree) to 7 (completely agree). The scale was tested for reliability using Cronbach Alpha and found to exhibit sufficient reliability (α=0.728, n=75).

5 Results

Across the two courses (BsF&C and MsSCM) and over the four years during which they were administered, student performance was consistently high, with passing rates ranging from 85% to 100% after a second opportunity. The majority of students obtained a grade equivalent to "very good" (8) or "good" (7) in the Dutch system, where 5.5 is considered a sufficient grade. A comparison with other courses offered concurrently showed that while students performed better in the data analytics course, they also exhibited higher degrees of attendance, and higher overall satisfaction with the course.

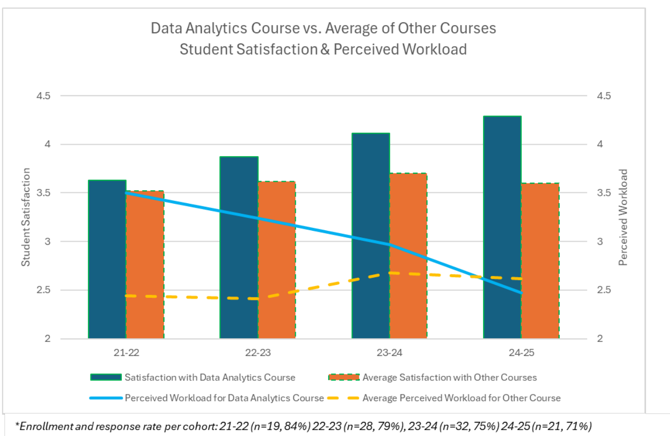
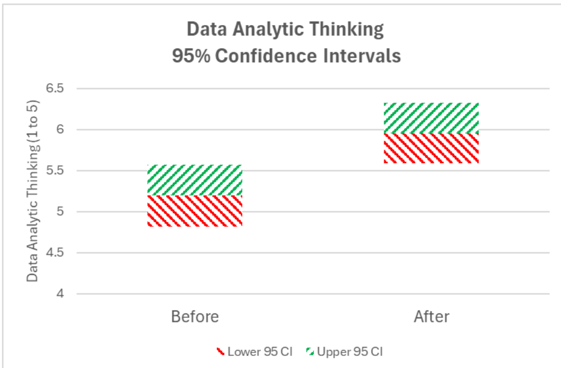


Figure 1: Comparison of Student Overall Satisfaction and Perceived Workload (MsSCM, cohorts 2-5)

Source: Own

As the course evaluation and perceived workload scores of the MsSCM across the last four cohorts indicate, students in earlier cohorts evaluated the course workload as higher than that of other concurrent courses, despite being more satisfied (Figure 1). Each year, measures were taken to decrease students' perceived workload. This was achieved primarily by reviewing formative and summative assessment moments and critically reviewing the assignment in relation to the learning objectives. As Figure 2 shows, the data analytics course contributed to improved students' data-analytic thinking, the primary learning outcome.



Number of respondents and response rate: before (n=36, 53%) and after (n=39, 50%)

Figure 2 - Data analytic thinking MsSCM students before and after data analytics course (4th year bachelor students vs MsSCM alumni)

Source: Own

5 Lessons Learned

Taken together, the experiences of our students, our own observations, and those of other instructors documented in the academic literature yielded several best practices that could assist others in developing data analytics courses for business students. In the section below, we discuss these and use student quotes from the course evaluations, reflection reports, and individual interviews as illustrations.

5.1 Treat R as a Black Box Application

While one of the strengths of the software R is its versatility, the learning curve for students without a background in computer programming or data analytics is steep (Echeverría et al., 2017; Msweli et al., 2023). To motivate these students, initially treating R as a black box application will help keep them motivated (Firth et al., 2021). This can be achieved by providing students with annotated scripts that create beautiful and informative graphs, thereby contributing to a "*wow look how awesome*" self-efficacy effect. At the start of each course, it is necessary to confirm that these scripts remain bug-free, especially after software and package updates. Instructors also need to ensure that the scripts provided to students can accommodate different date formats and decimal systems, especially when teaching international students. Students can thereby experience the advantages of R, with a less steep learning curve, less frustration, and thus a heightened sense of self-efficacy. As one student indicated on the mid-term student evaluation: "*R was very hard and I doubt if we are going to use that.*" However, after completing the course, this early resistance was replaced with a sense of achievement, as the student had "conquered" something difficult, stating, "*I really liked that we were forced to obtain some programming skills.*"

5.2 Create an Atmosphere of Collaborative Learning

Encouraging students to work together helps them mimic the professional world in which they will be operating. Furthermore, shared difficulties such as dealing with bugs in R code create camaraderie. Consistent with social constructivist theory, collaborative learning is therefore an important tool in supporting students as they learn data analytics (Firth et al., 2021); Vance et al., 2022). However, it remains crucial for instructors to be available to help students get "unstuck" in real time. Thus, supervising students as they work together and practice the concepts is a good use of class time (Firth et al., 2021). The students appreciated the opportunity to ask questions in real time. One student mentioned: "*We were guided a lot. You need to struggle to learn. We were able to ask questions quickly in learning to program.*" Whenever possible, teaching assistants should support instructors in responding to student questions (Hicks and Irizarry, 2018).

5.3 Use Relevant but Manageable Datasets and Examples

Consistent with the situated learning perspective (Vargas et al., 2024), course objectives should be clearly linked to the students' future professions, and examples and exercises should relate to sectors in which they are likely to work. Datasets should be chosen carefully and sources from companies that are attractive to students in product, service, or mission. The students then feel that they are working on relevant and timely business issues. As one student indicated on the course evaluation, "*it was great to work on a real-world case which was very timely.*" However, care needs to be taken to offer datasets that match their skills, to ensure an appropriate balance between effort and learning outcomes. By working on relevant cases and datasets, students can apply their existing domain knowledge and skills to their data analytics exercises, helping them make sense of course content. Students thereby see the added value of being acquainted with R for their future profession. As one student explained, "*The added value of* R *is learning to code as a finance specialist. This is very useful, even the basics, when you talk with the business analyst who built the model, and you can discuss. What I saw during my internship is that working with large datasets is part of business nowadays. That is what a controller does.*" Ideally, instructors should also be domain experts with data analytics expertise as they can help students bridge the gap between their domain expertise and newly acquired data analytics knowledge (Hicks and Irizarry, 2018; Tucker et al., 2022), as difficult as that may be (Msweli et al., 2023).

5.4 Introduce and Emphasize the Use of a Framework

Students greatly benefited from the systematic and efficient workflow enabled by the application of the CRISP-DM framework (Msweli et al., 2023). It allows students to translate business needs and objectives into questions that could be answered with data, and, conversely, to realize that results only hold value if they are implemented in the business context. The structured approach of CRISP-DM helped students in developing data analytic thinking (Provost and Fawcett, 2013) by clearly distinguishing between the domain expertise they already possessed and the technical expertise they were acquiring (Wirth and Hipp, 2000). Students also appreciated the challenge of embracing a new approach, and how it led them to gain more confidence: "Another main thing that I learned from this project is that it is good to be thrown into the deep sometimes with a challenge, or project in this case, that requires a whole new approach than what we have been used to in the last couple of years […]. I also feel that I can use this is my future career as well, because you can always get in a situation in which you do not specifically know how to approach it because your knowledge on the matter is scarce." Furthermore, graduates of the program reported that their knowledge of CRISP-DM was beneficial in their professional careers. As one graduate explained: "*it is great that when CRISP-DM comes up, I can contribute to the discussion*." For instructors who use their business experience to illustrate concepts, the CRISP-DM framework provides a way to structure their storytelling.

6 Conclusion and Future Work

Interest in data analytics is booming, and the need for business students to be proficient in this field remains strong. Academic programs aimed at domain experts should offer data analytics courses that leverage students' domain knowledge while accommodating their limited background in computer programming and statistics, thereby maintaining motivation through technically challenging yet accessible content. Drawing from the academic literature on the topic, student reflections, and our own experiences, we presented several lessons learned that may help other instructors develop similar courses. It is important to note that the course was developed in the context of the Dutch educational system, which is characterized by high industry involvement and oversight. The Dutch culture also values data-driven decision-making. Together, these factors ensured the needed legitimacy to invest resources in developing this course. This impetus and resources may not be available in other settings. However, we also acknowledge that the data science and data analytics fields are still developing rapidly, and therefore continuous monitoring and redesign of data analytics courses is necessary. For example, generative Artificial Intelligence (AI) tools (e.g. ChatGPT and Microsoft Copilot) are increasingly being used by students to help them code in R.

Our initial experience with allowing students to use AI to generate code is that it can help students who have already mastered basic programming concepts make progress more quickly. However, when students lack a solid understanding of basic R syntax, they struggle to use prompts effectively and to apply AI-generated code to their assignments. Although the quality of AI-generated code is rapidly improving, hallucinations (references to non-existent packages or functions) remain a persistent issue. This can lead to frustration among both students and instructors, as they often are unaware that hallucination is at play. Based on anecdotal evidence, we anticipate that as AI-generated code continues to improve, it will become an increasingly relevant educational tool. For now, however, further research is needed to explore how generative AI can best support student learning and to examine its associated ethical implications (Becker et al., 2023). Future course development should therefore critically assess the added value of these tools and consider how to integrate them effectively to enhance student learning outcomes.

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