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Teaching Data Analytical Skills to Business Undergraduates through GenAI-Augmented and Traditional Programming Tools

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Abstract

As data mining and predictive modeling skills become increasingly crucial, educators face challenges in selecting teaching tools that effectively balance technical depth, ease of use, and real-world applicability. This paper examines the use of Generative Artificial Intelligence (GenAI) augmented data mining tools, such as SAP Analytics Cloud, and compares their educational impact to traditional programming tools such as R. Through surveys, performance analysis over two terms, and instructor reflections, we explored how these tools affect learning outcomes and teaching practices differently in an undergraduate business school data mining course. We present a brief overview of GenAI and traditional programming tools, considering their respective strengths and limitations in educational contexts. We particularly examine how each type of tool influences the learning process, technical skill development, and students' ability to apply data mining concepts. This study offers insights into the effectiveness of GenAI-augmented and traditional teaching tools and presents pedagogical implications for educators seeking to optimize data analytical skills education in business schools. Unlike prior studies that examine programming tools or investigate GenAI in educational contexts separately, our work presents a direct contrast between the two approaches, allowing for a systematic comparison of their impacts on teaching and learning.

Keywords: Business Analytics Education, Data Literacy, Generative AI in Education, Student Learning Outcomes, Traditional Programming Tools, Tool Integration in Curriculum.

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1. INTRODUCTION

As firms lean on data for advantage, efficiency, and strategy, demand for strong data analysts is surging. Predictive modeling has become a core tool, used to forecast market trends, improve customer retention, and streamline operations (Layne, 2023).

Despite these advancements, significant gaps in data literacy remain. A recent report highlights that only 21% of the global workforce feels fully confident in their data literacy skills, and companies lose an average of five working days per employee annually due to data-related stress and inefficiencies (Simonet, 2020). A shortage of data literacy is a major barrier to realizing analytics' value, highlighting a gap between tech capabilities and workforce skills. Business education must treat data literacy as core and shift from theory-heavy curricula to hands-on training with practical tools and methods.

Business schools must balance technical depth with accessibility, integrating analytics with core business concepts. Because curricula blend analytical skills with practical application, tools that combine ease of use with rigor are best for diverse learners. As tools become more accessible, teaching must also emphasize interpreting and acting on insights. This paper examines how traditional programming and GenAI-augmented tools shape business analytics teaching and learning.

Traditional Programming Tools and Generative Artificial Intelligence Tools.

Traditional programming languages, particularly Python and R, remain foundational in both academia and industry for data analysis and predictive modeling (Johnson et al., 2020). Python's extensive libraries and readable syntax make it a popular teaching tool, while R's statistical foundations and packages support rigorous methods and visualization (Mehta, 2017; Tucker et al., 2023)**.** Interfaces such as RStudio, R GUI, and Jupyter Notebooks reduce the steep learning curve, making coding more accessible for students without technical backgrounds (Çetinkaya & Rundel, 2018; Software Sustainability Institute, 2021)**.** Still, many business students struggle with syntax and debugging before they can meaningfully engage in analysis, creating a trade-off between technical training and business-oriented analytical thinking (Harnowo, 2022; Wymbs, 2016)**.**

Recent advances in Generative AI (GenAI) introduce new possibilities for lowering these barriers. GenAI tools leverage large language models to generate insights, automate analysis, and support natural language interaction (Bommasani et al., 2021; Feuerriegel et al., 2024)**.** Platforms such as SAP Analytics Cloud (with Smart Discovery) and Power BI Copilot exemplify this shift, offering automated visualizations, pattern detection, and conversational interfaces (Microsoft, 2025; SAP PRESS, 2021)**.** For example, once specifying the data and key measures vs. master data, Smart Discovery can automatically generate dashboards, visualize charts, and provide insights in text. By automating routine tasks, GenAI may reduce cognitive load and free students to focus on higher-order skills like critical evaluation and problem-solving, fostering "hybrid intelligence as the integration of humans and AI, leveraging the unique Strengths of both" (Feuerriegel et al., 2024)

GenAI tools lower entry barriers, letting students move quickly to interpretation and application, but overreliance can promote superficial learning and limit technical depth. Traditional programming in R/Python is harder (syntax, debugging) yet builds analytical rigor and procedural problem-solving. Each cultivates different aspects of critical thinking, GenAI emphasizes evaluative/strategic reasoning, programming emphasizes technical/procedural, so educators should balance them to develop both conceptual insight and technical fluency.

Research Questions and Objectives

GenAI and traditional programming tools present trade-offs: GenAI offers accessibility and quick answers to business questions, while programming provides deeper technical understanding and flexibility. Our study asks how these approaches differently affect student learning outcomes, instructional efficiency, and perceptions in undergraduate business data

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mining, and what mix best integrates them in analytics education.

Our investigation focuses on comparing SAP Analytics Cloud (with GenAI features) and R GUI (traditional programming tool) in an undergraduate business data mining course over two semesters. Through this comparison, we aim to:

1. Compare the effectiveness of SAP Analytics Cloud and R GUI in supporting student mastery of regression-based data mining concepts, using lab assignments and exam performance as benchmarks.
2. Assess the impact of tool selection on student learning outcomes and instructional efficiency, drawing on survey responses, performance scores, and instructor reflections across the two semesters.
3. Evaluate the pedagogical implications of exposing students to both GenAI-augmented and traditional programming tools, based on student perceptions from surveys and comparative analysis of instructional time and learning results.

Through surveys, performance assessments, and instructor observations, we sought to understand not just which tool students preferred but how different tools shaped their learning experience and analytical capabilities. This paper presents our findings and their implications for business analytics education.

The remainder of this paper is organized as follows. Section 2 reviews prior research on programming tools in business education and emerging studies on GenAI in learning contexts, identifying the methodological gap our work addresses. Section 3 outlines the course design, instructional interventions, and data collection methods used to compare SAP Analytics Cloud and R GUI across two semesters. Section 4 presents survey results, performance analyses, and instructor reflections to assess student learning outcomes and tool effectiveness. Section 5 discusses the pedagogical implications of our findings, highlighting trade-offs between accessibility and technical depth. Finally, Section 6 concludes with key contributions, limitations, and directions for future research.

2. LITERATURE REVIEW

State of the art

While prior studies have examined programming tool use in business education (e.g., Python, R, or GUI-based environments), (Doyle et al., 2022; Porubän et al., 2024) and emerging research has explored GenAI in general learning contexts, (Alparslan, 2025; Chan & Hu, 2023; Fulara, 2024; Joshi, 2025a, 2025b; Kok Cha & Daud, 2025; Lin & Chen, 2024; Tu et al., 2024; Vieriu & Petrea, 2025) we found no studies directly comparing GenAI-augmented analytics platforms with traditional programming tools in undergraduate business data mining courses. This methodological gap is important because it leaves unanswered questions about how different tools influence both short-term learning outcomes and long-term skill development. By comparing SAP Analytics Cloud (with GenAI features) and R GUI in parallel classroom settings, our study provides one of the first empirical tests of this contrast.

The Rise of Data Analytics in Business and Education

Teaching data analysis for decision-making has become a curricular imperative for business schools. It has become increasingly established that business decisions should be grounded in data-driven insights rather than intuition. A growing body of empirical research demonstrates that firms that adopt data-driven decision-making (DDD) practices consistently outperform their peers in terms of productivity, asset utilization, and overall profitability. Brynjolfsson et al. (2011) in a seminal large-scale study of 179 publicly traded firms, found that DDD adoption was associated with 5–6% higher output and productivity, independent of IT spending and organizational structure. Comparable results in emerging economies, such as Gul et al. (2023) findings in Pakistan's banking sector underscore that the strategic benefits of DDD span diverse contexts.

These findings have prompted reforms across business curricula. Organizations expect business graduates to enter the workforce with fluency in data interpretation and modeling. Yet, achieving this in business programs, where students often lack a computer science background, requires pedagogical strategies that reach a balance between analytical rigor and accessibility. The question is no longer whether to teach analytics, but how best to teach it, especially to non-technical learners.

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Teaching Data Mining with Traditional Programming Tools in Business Education

Business undergraduates typically enter programming-heavy courses with a limited technical background, which can hinder learning when cognitive overload eclipses conceptual understanding. Doyle et al. (2022) details Temple University's experience introducing JavaScript to over 1,400 business students annually, noting that a significant portion of instructional time is spent introducing students to basic programming syntax and logic. This experience aligns with Luo & Adelopo (2024), who advocate for a student-focused pedagogy that brings together problem-solving and collaborative activities to make programming easier to learn. Still, challenges such as data wrangling, and debugging persist.

Porubän et al. (2024) propose task-driven case studies as a solution, enabling students to engage with real-world problems while avoiding poor programming practices. Despite these innovations, programming environments often impose a steep learning curve that risks alienating non-technical students or reducing the time available to explore high-level analytics concepts like clustering or regression. GUI-based environments such as RStudio have helped mitigate this issue, but the broader question remains: How can instructors ensure that students meaningfully learn to analyze data without becoming overwhelmed by code?

GenAI-Augmented Tools for Teaching Data Mining in Business Programs

Unlike traditional programming environments, GenAI-augmented tools reduce technical friction, allowing students to interact with data using natural language and generate visualizations or models with minimal manual coding. Tu et al. (2024) argues that LLMs are redefining the role of data scientists by shifting focus from syntax to strategic oversight. This evolution aligns with the shift in educational needs, where students must learn to manage AI-augmented tools rather than master every logical and technical detail.

Studies by Chan & Hu, (2023), Grájeda et al., (2023), Kovari, (2025), Lin & Chen, (2024) Ali et al. (2024) demonstrate how AI tools can enhance student engagement and comprehension. Effective results hinge on infrastructure, teacher training, and pedagogy, not just the tool. Ali's review underscores customization and ethics as core to responsible AI use. By generating insights from prompts and automating modeling, GenAI lowers technical barriers while helping students build the interpretive and critical thinking needed for decision-making.

Córdova et al. (2024) and Lin & Chen (2024) offer direct evidence from higher education settings, GenAI tools like ChatGPT can enhance creativity, reduce stress, and support autonomy, especially among learners with lower technical confidence. However, they also caution that overreliance on automation may limit deep understanding and critical thinking, concerns that should be included in curriculum design. These findings are complemented by Vieriu & Petrea (2025), who highlight both improved academic outcomes and ethical concerns, such as privacy and academic integrity. Together, these studies justify the use of GenAI as a complement, not a substitute, for analytical reasoning in business programs.

Tool Selection and Integration Strategies in Analytics Education

The decision to use GenAI-enhanced or traditional tools in analytics education, involves more than technical considerations, it reflects deeper pedagogical priorities. Research on tool integration suggests that blended models can yield the best results, especially when instructors intentionally build pedagogical structures that facilitate learning experiences. Kovari (2025) highlights the value of AI-driven personalization and collaborative learning in higher education, noting that multimodal learning environments supported by AI can enhance engagement and motivation.

From a curriculum design standpoint, frameworks such as Cognitive Load Theory and TPACK (Technological Pedagogical Content Knowledge) offer useful lenses. Gkintoni et al. (2025) synthesizes neuroscience and AI literature to argue that AI-powered systems, especially those that adapt based on cognitive state, can reduce mental load and optimize instructional pacing. While business education has not yet widely adopted neuroadaptive systems, the principle remains relevant: tools that reduce unnecessary complexity allow students to focus on high-value thinking. According to Bloom's Taxonomy, higher-order cognitive skills involve analysis, evaluation, and creation. GenAI tools, when integrated thoughtfully, may support these skills by enabling students to focus less on routine tasks and more on critical assessment and innovative problem-solving. However, overreliance on automation risks limiting opportunities for students to practice these higher-order skills.

Finally, insights from early education offer a broader pedagogical justification. Kok Cha &

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Daud (2025) find that AI tools boost early-childhood learning by reducing cognitive load and personalizing support. The pedagogical lesson generalizes: adaptive, scaffolded environments help learners of any age when first tackling abstract or technical content.

Existing studies have not directly compared GenAI tools like ChatGPT with R in business schools largely because R is a long-established programming language in analytics curricula, while GenAI has only recently emerged, and scholarship has not yet caught up. Research in business education has historically emphasized traditional tools such as R, Python, and Excel as core competencies (Aasheim et al., 2015; Johnson et al., 2020; Tucker et al., 2023) , whereas GenAI studies have mainly focused on student perceptions, creativity, and emotions in broader higher-education contexts (Chan & Hu, 2023; Córdova et al., 2024; Lin & Chen, 2024) . Methodological hurdles — such as the need to redesign curricula, address academic integrity concerns, and overcome disciplinary silos — further complicate systematic comparisons(Doyle et al., 2022; Luo & Adelopo, 2024) . In addition, GenAI has often been framed as an assistive rather than foundational skill (Feuerriegel et al., 2024; Tu et al., 2024) , making head-to-head contrasts with R less natural in prior research designs. Combined with the lag of peer-review cycles, these factors explain why direct R vs. GenAI comparisons in higher education have not yet appeared, leaving this gap open for timely investigation.

Business education should blend GenAI-augmented tools (for accessibility and engagement) with traditional programming in R/Python (for technical depth). Adoption must align with teaching goals, faculty readiness, and ethical standards, and future research should evaluate effects on learning outcomes, confidence, engagement, and long-term skill development. Table 1 compares the tools examined in this study.

Aspect	**GUI-based Tools (e.g., Tableau, SAP SAC)**	**Code-based Tools (e.g., R, Python)**
Ease of Use	User-friendly, drag-and-drop interfaces	Steeper learning curve, requires coding knowledge
Flexibility	Limited to built-in features and options	Highly flexible, customizable analyses and models
Learning Focus	Focus on interpretation and visualization	Focus on programming, logic, and statistical rigor
Reproducibility	More difficult to fully reproduce workflows	Easily reproducible with scripts and version control
Scalability	Best for small-to-medium datasets	Handles large datasets, advanced models, automation

Table 1 Comparison GenAI vs. Traditional Tools

3. METHODOLOGY

Course Structure and Design

Business Intelligence is an undergraduate elective course that covers both data warehousing and mining components offered at a private university in the northeast of U.S. The course is organized into sequential modules, introducing students to increasingly sophisticated data analysis techniques. This study focuses specifically on the 3-week data mining module, which introduces students to predictive modeling through regression analysis. The module was designed to progressively build students' understanding from theoretical foundations to practical implementation, with learning objectives focused on understanding fundamental regression concepts, mastering predictive model construction, developing model evaluation skills, and applying these techniques to business problems. Its detailed learning objectives are available upon request.

The module follows a structured three-phase approach. The first phase establishes conceptual foundations through lectures covering regression concepts, metrics, and business applications. The second phase provides guided practice through a hands-on lab, allowing students to apply theoretical concepts in a controlled environment. The final phase consists of an assignment, where students demonstrate their acquired skills in a new context.

In Fall 2022, the module exclusively used R GUI in the lab activities. The lab structure included background slides introducing the lab, tutorial

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slides with R-specific instructions, and step-by-step guided practice using the R GUI. After the lab demonstration, students completed their lab assignments, with questions designed to test both technical implementation and conceptual understanding.

The Spring 2024 implementation integrated both SAP Analytics Cloud (SAC) and R GUI into the curriculum, which was systematically developed. The instructor completed formal training in SAP and obtained a badge in analytics and revised the curriculum in response to feedback from the institution's Center for Teaching Excellence.

Component	**Fall 2022**	**Spring 2024**
Course Content	Regression model, analysis through code-based analysis with GUI	Regression model, analysis through code-based analysis with GUI and Augmented intelligence tool
Lecture Materials	Regression slides	Same regression slides
Lab Activities	Wine price analysis using R GUI	Wine price analysis using both SAP SAC and R GUI
Lab Support Materials	• Background slides • R tutorial slides • Step-by-step R GUI instructions	• Same background slides • SAC tutorial materials • Step-by-step SAC instructions • R tutorial slides • Step-by-step R GUI instructions
Assessment by lab assignment and final exam	Questions focusing on analysis and interpretation	Same questions focusing on analysis and interpretation

Table 2. Implementation in Fall 2022 and Spring 2024

The SAP badge assures us that the instructor has an in-depth understanding of SAC. The lab retained the same analytical content but was enhanced with tutorials and step-by-step guides for both tools. New SAC-specific materials supported its integration. The assessment questions remain consistent to ensure comparability. A set of the same data mining questions was also administered in the final exam in both semesters. The Spring 2024 dual-tool approach aimed to expose students to both traditional programming and GenAI-augmented tools, enabling a direct comparison of learning outcomes and expanding students' analytical skills. Table 2 details the differences between semesters, outlining lecture content, lab structure, and exam requirements, forming the basis for evaluating the impact of tool choice on student learning.

Student populations of Fall 2022 and Spring 2024 are comparable. In Fall 2022, the class has 24 students. 11.7% are SCM, 11.7% are marketing, 11.7% are finance, and the rest are IST students. 41.2% have GPA between 3 and 3.5, and 53.3% have GPA above 3.5. In Spring 2024, the class has 24 students. 20% are SCM, 26.7% are marketing, 6.7% are management, 6.7% are finance, and the rest are IST students. 40% have GPA between 3 and 3.5, and 40% have GPA above 3.5.

Data Collection

Data was collected through surveys and performance scores on lab activities and final exam questions.

Surveys

Two structured surveys were administered through Canvas to assess students' experiences with the analytical tools in Spring 2024. Both surveys required course activities with non-anonymous responses to ensure completion and enable connection with performance data. The first survey (GenAI Survey, 0.2% of total course score) was conducted immediately after students completed their first SAC module, while the second survey (R and SAC Comparison Survey, 0.15% of total course score) was administered after the data analysis module.

The GenAI Survey focused on students' experience with SAC and its GenAI features. The survey included ten questions designed to assess three key areas: prior experience with analytics tools, user experience with SAC's Smart Discovery feature, and attitudes toward GenAI tools in data mining. Questions explored students' confidence in creating business intelligence reports, perceived difficulties in implementation, and their evolving attitudes toward GenAI tools in data analysis.

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The R and SAC comparison survey, administered after students had experience with both tools, contained eight questions examining tool preferences and learning outcomes. The survey investigated students' perceptions of how each tool contributed to their understanding of predictive modeling, their preferences between the tools, and specific likes and dislikes about each platform.

Table 3 summarizes the key areas of investigation in each survey. Details of the survey questions can be found in the appendix.

Survey	Timing	Focus Areas	Key Questions
GenAI Survey	After completing SAC introduction and lab	• Prior tool experience • Smart Discovery implementation • GenAI attitudes	• Tool familiarity • Implementation difficulty • Confidence in BI reporting • Future GenAI adoption
R and SAC Comparison	End of Data Mining module	• Tool comparison • Learning outcomes • Background information	• Tool preferences • Learning effectiveness • Tool-specific feedback • Programming experience

Table 3. Survey Details

Lab Activities

The hands-on lab reinforced theory through practical predictive modeling using a real-world dataset with variables like temperature, rainfall, wine age, and population, aiming to predict wine prices. Students began with data exploration and single-variable regressions, then built multiple regression models to improve accuracy. They evaluated models using metrics like R-squared and RMSE, alongside GenAI insights, and made final predictions. In Fall 2022, students used R GUI exclusively, supported by background materials, tutorials, and guided practice in interpreting results and making data-driven recommendations.

In Spring 2024, the lab used both SAC and R GUI, allowing students to compare traditional and GenAI-augmented methods through the same wine price analysis. SAC tutorials emphasized Smart Discovery and automated features. Students were assessed on implementing regression models, interpreting results, making evidence-based predictions, and comparing approaches. This setup enabled direct comparison of learning outcomes while keeping core objectives consistent.

4. RESULTS

Survey Results

The GenAI survey revealed evolving attitudes toward AI-augmented analytics tools. Students reported significantly increased confidence in their ability to generate comprehensive business intelligence reports when using GenAI features. They noted reduced time requirements for comprehensive analyses and improved their ability to understand the business implications of their findings.

Students struggled with GenAI's prompt design and validating automated insights—highlighting the need to balance automation with critical thinking. Even so, surveys showed GenAI lowered technical barriers and was viewed positively, with students valuing a blend of GenAI and traditional methods and seeing these combined skills as important for their careers.

Using both tools led to deeper learning: SAC was preferred for its intuitive, visualization-rich, business-oriented interface, while R GUI offered greater control and analytical depth but came with setup hassles, package issues, and a steep learning curve. Many students had prior Python experience but little exposure to SAC/BI tools. Overall, students favored GenAI-augmented tools for ease and speed yet recognized programming's value for building strong analytical skills, suggesting a blended approach best supports understanding and practical application in data mining.

Performance Analysis

Performance analysis was conducted using two assessments. The first compared student lab activity outcomes across semesters (Spring 2024 post-implementation vs. Fall 2022 pre-implementation) and within Spring 2024 between R and SAC labs. The second compared student

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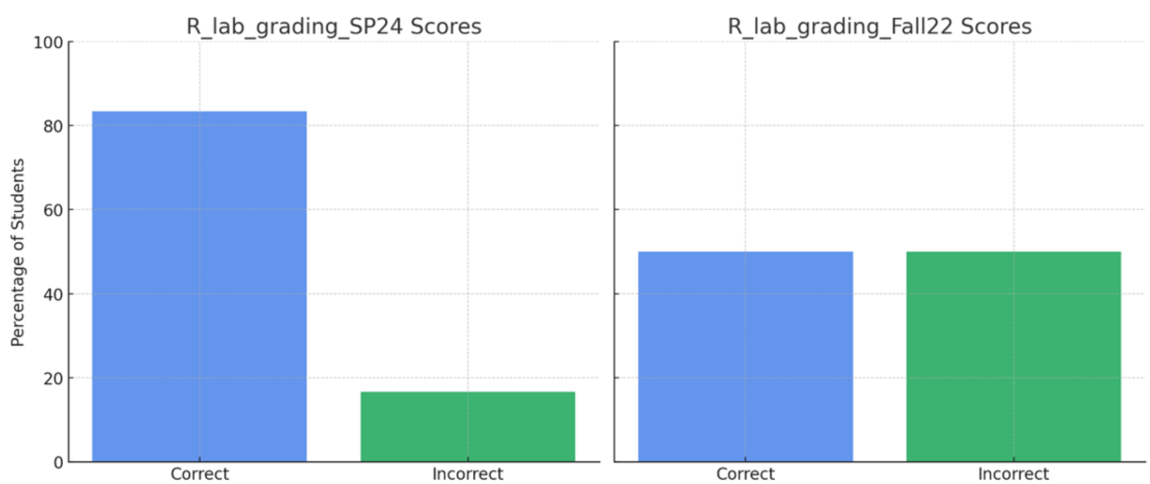
performances on an identical set of final exam questions. To ensure objective and consistent grading, one of the authors who did not teach this course yet has expertise in data mining and GenAI also evaluated all the lab activities and final exam answers in both semesters. Discussions were held until a consensus was reached.

Specifically, in terms of R lab activities, students in Spring 2024 demonstrated significantly higher average performance as compared to Fall 2022 ($t=2.56$, $p=0.014$), with less variation in scores (1.9 in Spring 2024 compared to 2.6 in Fall 2022, on a 0-5 scale) despite receiving the same amount of lecture time and lab activity duration. Table 3 illustrates this comparison. We note that the student population of these two cohorts is comparable as reported beforehand, and the assessment questions of all lab activities across semesters are the same. The observed improvement in student learning is likely attributed to the integration of SAC in Spring 2024, which facilitated the instruction and delivery of data mining concepts and skills.

We further analyzed student performance between the student R lab and the SAC lab in Spring 2024. Not surprisingly, given that SAC was presented first, students performed better in the R lab than SAC ($t=4.41$, $p=0.0002$) as reported in Graph 1. This is consistent with the conventional wisdom that repetitive exposure can reinforce learning.



Note: the left/right chart shows the percentage of students who get questions correct and incorrect in Spring 2024/Fall 2022

Graph 1. Comparison of student performance in R lab activities

The current research found that reducing technical barriers through GenAI-augmented tools can enhance student learning outcomes, particularly among non-technical business students. The observed improvement in Spring 2024 performance on R lab activities mirrors the literature's assertion that GenAI platforms such as reducing cognitive load and increase accessibility (Lin & Chen, 2024; Tu et al., 2024). This alignment supports the claim by Grájeda et al. (2023) and Vieriu & Petrea (2025) that GenAI tools promote autonomy and reduce stress, leading to greater productivity, consistency, and performance in academic tasks. Moreover, these findings emphasize the importance of balancing technical skill acquisition with conceptual understanding. Thoughtful SAC integration in Spring 2024 let students focus on analysis rather than coding, yielding performance gains. These results empirically support the literature's call to strategically use GenAI tools to improve learning and serve diverse learners in business analytics programs.

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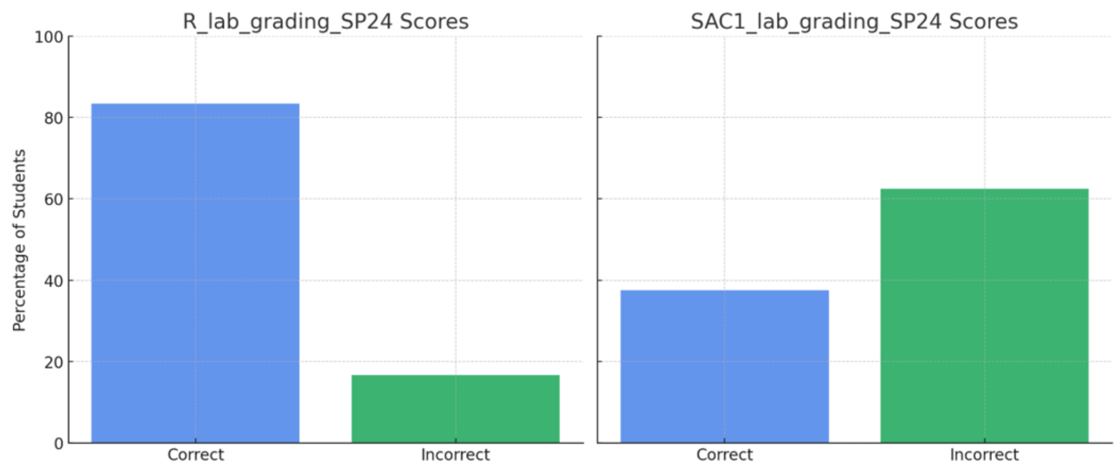


Note: the left/right chart shows the percentage of students who get questions correct and incorrect in Spring 2024

Graph 2. Comparison of student performance in R and SAC lab activities

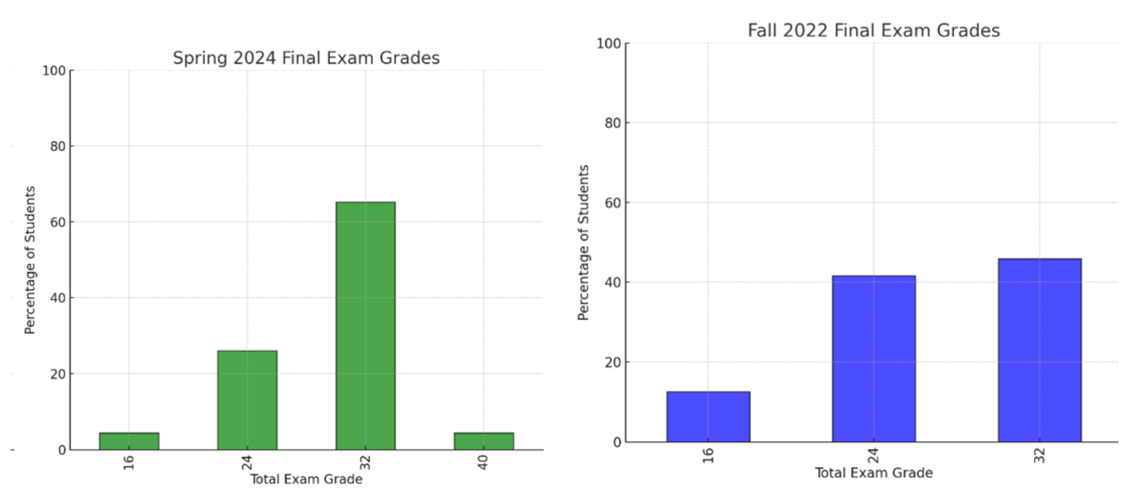
The results from our second assessment echo the above findings. Analysis of the final exam questions (Graph 3) indicates that Spring 2024 students achieved a higher average score than their Fall 2022 counterparts (p=0.07). This statistical significance indicates meaningful improvements in learning. Furthermore, the standard deviation of student performance was lower in Spring 2024 than in Fall 2022. This exciting finding is likely due to the introduction of SAC, a GenAI-augmented data mining tool.

Instructor Reflections

The integration of SAC and R GUI into the curriculum provided a unique opportunity to observe how these tools shaped both the student learning experience and instructional practices. Each tool presented distinct strengths and challenges, which highlighted the trade-offs educators face when choosing tools.

SAC's no-code, Power BI/Tableau–like interface (e.g., Smart Discovery) made labs smoother and lower-stress, letting students focus on concepts and strategic analysis. By contrast, R GUI required coding steps (scripts, data wrangling, package issues), which proved challenging, especially for non-programmers, and demanded extra troubleshooting even from experienced students.

Student support needs varied: SAC's user-friendly design reduced one-on-one coaching and encouraged peer help, whereas R's technical complexity (coding, package installs) led to frequent instructor assistance, making R labs far more support-intensive in and out of class.



Note: the left/right chart shows the percentage of students at various score levels in Spring 2024/Fall 2022. The full score is 40.

Graph 3. Comparison of data mining questions in Final exams

5. DISCUSSION

This pedagogical study deals with the issues of tool selection, technical depth, and real-world application. This includes questions of both tool depth versus breadth and the conceptual understanding of the business domain versus hands-on execution using tools. Decisions an instructor must make should be based on pedagogical priorities, which require balancing competing learning objectives. These types of choices are not limited to the context of data mining education but are widely generalizable across learning environments.

Using multiple tools creates a depth-versus-breadth trade-off, but the variety can better support diverse learners. Beyond tool choice, cultivating human–AI collaborative problem-solving is becoming increasingly essential.

To be employable, students must develop the skills needed to be fluent in using GenAI. This fluency includes the ability to write meaningful GenAI prompts. Prompt writing should be emphasized throughout university curricula. Furthermore, the effectiveness, intelligence, and ease of use of AI augmentation is expected to increase at an exponential rate. Thus, the use of AI augmented tools, like SAC, is not just a means to learn new concepts, like data analysis, it is a skill students must master to participate in the emerging Workforce 5.0.[1]

6. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

This study provides valuable insights into the use of GenAI-augmented tools and traditional programming platforms in business analytics education. It used a survey, performance assessments, and instructor reflection to specifically compare the effectiveness of using traditional programming tools (R-GUI) to GenAI augmented tools (SAC). It also raises the issue of the effectiveness of using multiple tools, in a serialized fashion, to reinforce concepts. Our results showed that the use of a traditional programming tool, R-GUI, offers greater control and flexibility to students. However, R-GUI has a steep learning curve, and it is difficult to set up the programming environment. Those with a coding background were more capable of tackling R-GUI without issue. Thus, student backgrounds should be a key factor in tool choice.

The GenAI augmented tool, SAC, enhances the students' understanding of the analyses, increases their confidence in performing the analyses, and allows them to become productive more quickly. However, designing good prompts in SAC proves to be challenging. Overall, there is a clear student preference for using SAC. We found that the assessment of student performance when using R-GUI, in a lab assignment (Fall 2022), improves when it is preceded by a SAC lab assignment (Spring 2024). We also observe that students' overall understanding of data mining and analyses concepts increases when both tools are used.

However, several limitations should be considered when interpreting the findings. First, the results are generated in the context of an undergraduate business school and need to be generalized to other disciplines or educational levels with caution. Additionally, the focus on SAC and R GUI represents a subset of the available tools for teaching data analytics. Other tools with distinct features, such as Python with Jupyter Notebooks, could yield different insights and learning experiences. Second, this study compares the learning outcomes of two semesters, which may not fully capture the long-term impact of tool use. The reliance on self-reported survey data also introduces potential biases, as students may overestimate their confidence or minimize challenges due to social desirability bias. Furthermore, the performance metrics used in this study might not comprehensively measure students' conceptual understanding or practical proficiency and may be influenced by potential grader bias. Future studies should also investigate the relative importance of GenAI tool and the repeated practice.

Future work should use longitudinal studies to assess GenAI tools' long-term effects on learning and career outcomes, and broader comparisons to evaluate more analytics platforms. It should also reflect the 2025 shift to augmented AI collaborative, dialogic systems that work alongside humans, ask clarifying questions, deepen human reasoning, and improve via continuous feedback.

REFERENCES

Aasheim, C. L., Williams, S., Rutner, P., & Gardiner, A. (2015). Data Analytics vs. Data Science: A Study of Similarities and Differences in Undergraduate Programs Based on Course Descriptions. *Journal of Information Systems Education*, *26*(2), 103–115.

Ali, O., Murray, P. A., Momin, M., Dwivedi, Y. K., & Malik, T. (2024). The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technological Forecasting and Social Change*, *199*. https://doi.org/10.1016/j.techfore.2023.123076

Alparslan, A. (2025). The Role of Accuracy and Validation Effectiveness in Conversational Business Analytics. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3540975

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., Bernstein, M. S., Bohg, J., Bosselut, A., Brunskill, E., Brynjolfsson, E., ..., & Liang, P. (2021). On the Opportunities and Risks of Foundation Models. *ArXiv Preprint ArXiv:2108.07258*. https://doi.org/10.48550/arXiv.2108.07258

Brynjolfsson, E., Hitt, L., & Kim, H. H. (2011). *Strength in Numbers: How does data-driven decision-making affect firm performance?* https://doi.org/10.2139/ssrn.1819486

Çetinkaya-Rundel, M., & Rundel, C. W. (2018). Infrastructure and Tools for Teaching Computing Throughout the Statistical Curriculum. *The American Statistician*, *72*(1), 58–65. https://doi.org/10.1080/00031305.2017.1397549

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-023-00411-8

Córdova, P., Grájeda, A., Córdova, J. P., Vargas-Sánchez, A., Burgos, J., & Sanjinés, A. (2024). Leveraging AI tools in finance education: exploring student perceptions, emotional reactions and educator experiences. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2431885

Doyle, M., Lavin, A., & Sclarow, S. (2022). *Association for Information Systems Association for Information Systems Teaching Programming to 1,400 Business Students per year Teaching Programming to 1,400 Business Students per year*. https://aisel.aisnet.org/treos_amcis2022/17

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering*, *66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-7

Fulara, A. S. (2024). Comparative Analysis of Artificial Intelligence (GenAI) in Business Intelligence Platforms. *International Journal of Computer Trends and Technology*, *72*(4), 95–101. https://doi.org/10.14445/22312803/ijctt-v72i4p112

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging Cognitive Load Theory: The Role of Educational Neuroscience and Artificial Intelligence in Redefining Learning Efficacy. In *Brain Sciences* (Vol. 15, Issue 2). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/brainsci15020203

Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2023). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2023.2287917

Gul, R., Leong, K., Mubashar, A., Al-Faryan, M. A. S., & Sung, A. (2023). The Empirical Nexus between Data-Driven Decision-Making and Productivity: Evidence from Pakistan's Banking Sector. *Cogent Business and Management*, *10*(1). https://doi.org/10.1080/23311975.2023.2178290

Harnowo, A. S. (2022). Blending a MOOC course into a Business School's Course to Introduce Python for Data Analytics. *Business Education Innovation Journal*, *14*(2), 31–36.

Johnson, M. E., Albizri, A., & Jain, R. (2020). Exploratory analysis to identify concepts, skills, knowledge, and tools to educate business analytics practitioners. *Decision Sciences Journal of Innovative Education*, *18*(1), 90–118. https://doi.org/10.1111/dsji.12195

Joshi, S. (2025a). *Review of Gen AI Models for Financial Risk Management*. https://doi.org/10.32628/CSEIT2511114

Joshi, S. (2025b). *The Transformative Role of Agentic GenAI in Shaping Workforce Development and Education in the US*. https://ssrn.com/abstract=5133376

Kok Cha, W., & Daud, P. (2025). Enhancing Early Education with Artificial Intelligence: A Comparative Study of AI-Powered Learning Versus Traditional Methods. *International Journal of Academic Research in Business and Social Sciences*, *15*(2). https://doi.org/10.6007/IJARBSS/v15-i2/24690

Kovari, A. (2025). A systematic review of AI-powered collaborative learning in higher education: Trends and outcomes from the last decade. In *Social Sciences and Humanities Open* (Vol. 11). Elsevier Ltd. https://doi.org/10.1016/j.ssaho.2025.101335

Layne, R. (2023, May 31). With predictive analytics, companies can tap the ultimate opportunity: Customers' routines. *Harvard Business School Working Knowledge.* https://www.library.hbs.edu/working-knowledge/with-predictive-analytics-companies-can-tap-the-ultimate-opportunity-customers-routines

Lin, H., & Chen, Q. (2024). Artificial intelligence (AI) -integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes. *BMC Psychology*, *12*(1). https://doi.org/10.1186/s40359-024-01979-0

Luo, X., & Adelopo, I. (2024). Exploring pedagogies, opportunities and challenges of teaching and learning programming in business school. *Journal of International Education in Business*. https://doi.org/10.1108/JIEB-05-2024-0060

Mehta, A. (2017). *How to Choose the Right Programming Language for Analytics*. https://www.analyticsinsight.net/insights/want-to-choose-right-programing-language-here-is-a-guide/

Microsoft. (2025). *Overview of Copilot for Power BI*. https://learn.microsoft.com/en-us/power-bi/create-reports/copilot-introduction

Porubän, J., Nosál', M., Sulír, M., & Chodarev, S. (2024). Teach Programming Using Task-

ISSN: 2473-4901
v11 n6350

Driven Case Studies: Pedagogical Approach, Guidelines, and Implementation. *Computers*, *13*(9), 221. https://doi.org/10.3390/computers13090221

SAP PRESS. (2021). *An Overview of SAP Analytics Cloud Smart Assist and Smart Predict Services*. https://blog.sap-press.com/an-overview-of-sap-analytics-cloud-smart-assist-and-smart-predict-services

Simonet, K. (2020, June 9). *Why data literacy is a key ingredient to success in the age of data and analytics: And how to unlock its value: The essential roles of measurement and data culture.* Deloitte Belgium. https://www.deloitte.com/be/en/services/consulting/analysis/data-literacy-is-key-to-success.html

Software Sustainability Institute. (2021). *GUIs for Research Software: Why Are They Relevant? (Part One)*. https://www.software.ac.uk/blog/guis-research-software-why-are-they-relevant-part-one

Tu, X., Zou, J., Su, W., & Zhang, L. (2024). What Should Data Science Education Do With Large Language Models? License: Creative Commons Attribution 4.0 International License (CC-BY 4.0). *Harvard Data Science Review • Issue*, *6*(1), 2024. https://doi.org/10.1162/99608f92.b007ab

Tucker, M. C., Shaw, S. T., Son, J. Y., & Stigler, J. W. (2023). Teaching statistics and data analysis with R. *Journal of Statistics and Data Science Education*, *31*(1), 18–32. https://doi.org/10.1080/26939169.2022.2089410

Vieriu, A. M., & Petrea, G. (2025). The Impact of Artificial Intelligence (AI) on Students' Academic Development. *Education Sciences*, *15*(3). https://doi.org/10.3390/educsci15030343

Wymbs, C. (2016). Managing the innovation process: Infusing data analytics into the undergraduate business curriculum. *Journal of Information Systems Education*, *27*(1), 61–74.

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Appendix: Survey Questions

GenAI Survey

Have you used SAP Analytics Cloud prior to this course?

Have you used any other tools that can auto generate several pages of visualization reports including key influencers, simulation, and descriptive charts, with a few clicks?

If this SAC was not provided, how long do you think will it take you to complete a similar BI report that can answer all the questions? Reminder: those questions are related to Key Influences, Simulations, and descriptive summary.

How difficult is it to implement the Smart Discovery in this lab?

How difficult is it to use the story created by Smart Discovery to answer data and business questions in the assignment?

To what extent does the GenAI functionality, i.e., Smart Discovery in SAC, help you feel confident that you are able to provide an insightful BI report that goes beyond just descriptive summary and charts, as compared to using tools without it?

You can choose multiple answers. What are the challenges in using Smart Discovery in creating meaningful and in-depth BI report?

After this experience, have your attitude towards using GenAI tool in data mining changed?

Will you embrace GenAI tools for data mining in the future? Choose the best that describes your attitude.

Do you agree that GenAI tools help prepare people qualified for various data mining tasks with considerable less technical barriers and better efficiency?

R and SAC Comparison Survey

How do you think learning these two tools, SAC and R GUI, help you learn designing, applying, and comparing predictive models?

If we only had time to learn one tool, which one would you select? Why?

What did you like about SAC in this module?

What did you dislike about SAC in this module?

What did you like about R GUI in this module?

What did you dislike about R GUI in this module?

What is(are) your major(s), and track if any?

Have you taken any programming related courses? If yes, what is the course and the used programming language?