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Integration of a Collaborative Artificial Intelligence in Improving Student Learning Outcomes in Data Analytics

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Abstract

Generative Artificial Intelligence (GenAI) tools commonly used in higher education predominantly support one-to-one interactions between learners and technology, with limited emphasis on collaborative learning. This non-equivalent quasi-experimental study investigated the effects of integrating collaborative GenAI on students' learning outcomes in a data analytics course within a Philippine higher education institution. Using a free and open-source statistical software, pre- and post-assessments were administered to evaluate students' academic performance. Findings from a one-way analysis of covariance indicated a significant improvement in students' levels of mastery across the experimental groups following the implementation of the collaborative GenAI-assisted intervention. Further analysis using one-way analysis of variance revealed significant gains in students' problem-solving, critical thinking, and written communication skills. The results provide empirical evidence supporting the pedagogical value of collaborative GenAI in enhancing higher-order learning outcomes. The study offers implications for curriculum design, instructional practices, faculty development, and policy formulation in higher education amid ongoing digital transformation.

1 Introduction

From a global perspective, Generative Artificial Intelligence (GenAI) has rapidly transformed the educational landscape by reshaping how students and educators' access, process, and engage with information online. Recent studies indicate that over 90% of higher education students utilize GenAI tools to explain concepts, summarize articles, check grammar, generate research ideas, create digital content, and more (Freeman, 2025; Kelly, 2024; Hwang & Lee, 2025). These students are increasingly drawn to GenAI for its capacity to provide immediate, context-aware responses. Moreover, Wu and Yu (2023) emphasized that GenAI plays a transformative role in shaping students' learning outcomes. The integration of GenAI into teaching and learning not only enhances student engagement and personalizes learning experiences but also fosters critical thinking, creativity, and problem-solving skills. By enabling more adaptive and interactive learning environments, GenAI holds the potential to improve students' academic performance significantly. In addition, Chen et al. (2023) underscored the role of GenAI in facilitating collaborative knowledge building among students. Their findings revealed that GenAI can serve as a cognitive partner in group learning settings, enhancing communication, co-construction of knowledge, and mutual understanding through intelligent prompts, feedback, and idea generation. Particularly in the fields of mathematics and statistics, students are leveraging these tools for problem-solving, personalized tutoring, adaptive feedback, and task customization (Von Garrel & Mayer, 2023; Walkington & Bainbridge, 2025; Matzakos et al., 2023; Song et al., 2024). These tools are seen to provide targeted support by addressing individual learning needs, providing step-by-step solutions, and dynamically adapting tasks based on learners' progress. It is seen to enhance both comprehension and performance in quantitative disciplines. In support, Eith and Zawada (2025) reported that postgraduate students use GenAI as a conversational learning companion in statistics courses to alleviate anxiety and reinforce critical thinking. Similarly, Megahed et al. (2024) described how GenAI tools helped students perform statistical analyses and deepen their conceptual understanding. Notably, these students

continue to apply their prior knowledge to critically assess the accuracy and relevance of GenAI-generated content in the field of mathematics and statistics. Despite these advancements, existing studies also observed that student interactions with GenAI tend to be non-collaborative with their fellow students, an aspect this study aims to further examine and address, particularly in statistics education.

Corollary, there is a growing need for teachers to acknowledge and understand how students are utilizing GenAI tools to enhance their learning processes, develop critical academic skills, and engage more meaningfully in both individual and collaborative learning contexts. Teachers themselves are increasingly adopting GenAI to streamline administrative tasks, support personalized instruction, improve content delivery, and enhance the assessment of student competencies across various educational levels (Hamilton, 2023; Hwang & Lee, 2025; Yang et al., 2025; Kim, 2023). In support, Labadi and Ly (2025) emphasized the integration of GenAI in course-based projects as a means to enhance student engagement and learning outcomes. These projects often capitalize on GenAI's capabilities in idea generation, content organization, and task automation, enabling students to develop creative outputs, explore complex problems, and engage in deeper analytical thinking. By incorporating GenAI into project-based learning, educators are able to foster a more dynamic, inquiry-driven classroom environment that supports both innovation and independent learning. Meanwhile, Uygun (2024) reported generally positive attitudes among teachers toward the integration of GenAI tools in both teaching and assessment practices. GenAI was seen as a valuable instructional aid capable of enhancing lesson planning, generating differentiated learning materials, and providing immediate feedback to students. Additionally, teachers acknowledged its potential in creating more efficient and fair assessment systems through automated grading and formative feedback mechanisms. These favorable perceptions suggest a growing openness among educators to explore AI-driven innovations, provided that appropriate training, ethical safeguards, and institutional support are in place (Fowler, 2023; Basit, 2025; Wong, 2024; Pratiwi et al., 2025; Yusuf et al., 2024).

Early studies on the integration of GenAI tools in statistics education have documented how educators are beginning to utilize these technologies in various instructional tasks, including the development of course materials, the creation of exam questions, and the generation of code for statistical software such as SAS, Python, and R (Rasul et al., 2023; Ellis & Slade, 2023; Xing, 2024). Schwarz (2025) further highlighted how GenAI tools can support individuals with limited statistical knowledge and experience by facilitating data analysis processes. By simplifying complex analytical tasks, GenAI makes data analysis more accessible and manageable for a wider range of students. This democratization of data-driven inquiry holds significant implications for teaching research methods and advancing data literacy across academic disciplines.

Despite the growing interest in integrating GenAI into statistics education, there remains a lack of empirical research examining its actual impact on student learning outcomes. This is particularly evident in classroom-based applications that utilize free and open-source statistical software (FOSS), where practical insights into GenAI's pedagogical value remain scarce, especially within the Philippine context. Canlas (2019) noted that the teaching of statistics and data analysis in the Philippines continues to rely

heavily on traditional methods, with limited integration of digital tools and emerging learning technologies. This reflects a persistent gap between global technological advancements and actual classroom implementation in the country. This gap becomes even more pressing when considering that one of the key competencies highlighted in national policy frameworks such as the Philippine Qualifications Framework (PQF) and the Philippine Skills Framework (PSF) is data analysis (Melchor et al., 2023). These frameworks aim to align educational outcomes with the evolving demands of the workforce, yet the underutilization of GenAI and digital tools in classroom practice suggests a disconnect between policy aspirations and educational realities.

As educational systems begin to reimagine teaching, learning, and assessment through the lens of GenAI integration, this transformation continues to be hindered by systemic challenges such as limited infrastructure, insufficient teacher preparedness, and the absence of localized frameworks for GenAI implementation. These barriers underscore the urgent need for context-specific, evidence-based strategies to meaningfully integrate GenAI into Philippine classrooms, particularly in the field of statistics education. Building on these discussions, this study examines how the integration of a collaborative GenAI tool and FOSS can improve student learning outcomes in a data analytics course offered by a private higher education institution (HEI) in the Philippines, specifically the adoption of a collaborative GenAI tool. This tool is a web-based platform designed and developed to support exploration and facilitate collaboration with GenAI in educational contexts, providing students with a structured environment to engage with AI in meaningful, pedagogically guided ways. Corroborating this, the study is grounded in two complementary theoretical frameworks: the Substitution, Augmentation, Modification, and Redefinition (SAMR) model by Puentedura (2020) and the AI Policy Education Framework by Chan (2023). The SAMR model provides a lens for guiding and assessing the integration of technology into instructional practices in higher education. Meanwhile, the adapted AI Policy Education Framework ensures that technology adoption aligns with broader institutional and developmental goals, particularly in terms of AI readiness, literacy, ethical use, and responsible implementation in educational settings. Specifically, the study sought to answer the following research questions:

1. What is the effect of integrating a collaborative AI tool on students' learning outcomes in performing data analytics?
2. How do students perceive the role of a collaborative AI in supporting their learning of data analytics?

2 METHODS AND DESIGN

A nonequivalent quasi-experimental research design was employed to continually work within the natural classroom environment and structures. This allows for a systematic exploration of the effects of a collaborative GenAI in learning data analytics with statistical software through multiple data-gathering approaches (Gopala et al., 2020; Kim & Clasing-Manquian, 2023; McCombes, 2023; Cresswell, 2014).

The study was conducted in a Philippine private HEI. Purposefully, respondents were selected based on specific inclusion criteria. Respondents had to meet the following criteria: (1) be officially enrolled in the course and have completed the Philippine Senior High School program; (2) hold regular academic status in their respective degree programs; (3) be enrolled in a course that does not require prior knowledge or proficiency in prompt engineering; (4) belong to class sections that were pre-assigned by the institution and handled by the same teacher or facilitator; and (5) have access to the necessary resources to participate in the course, including a personal laptop and a stable internet connection. Table 1 below shows the distribution of respondents categorized as control and experiment groups, respectively.

Table 1
Distribution of students in each group

Groups	Number of Students	Description
Control Group	45	No GenAI integration No Prompt Engineering Session
Experimental Group 1	43	With GenAI integration, Prompt engineering session
Experimental Group 2	38	With GenAI integration No Prompt Engineering Session
Total	126	

A multi-tiered system was designed to ensure a structured and systematic approach in conducting this study. Tier 1 focused on the development and validation of the learning materials and research instruments, ensuring their alignment with the study's objectives, the SAMR model, and the AI policy education framework. Tier 2 involved the implementation of the quasi-experimental design through a pre-and post-assessment model. Tier 3 concentrated on data analysis, synthesizing collected data to evaluate the impact of the intervention and draw meaningful conclusions.

Tier 1. Development and validation of research instruments and learning materials

The preparatory phase focused on developing and validating research instruments and learning materials used for this study. The first research instrument was used to gauge the academic performance of the students in learning the competencies and skills of performing data analysis using a FOSS during the pre-and post-assessment phase of the study. This covers exploratory data analysis, comparative analysis, correlational analysis, and regression analysis. Conventional test development was observed (Costa, 2023; Butler, 2018). A Table of Specifications and 100 multiple-choice questions for the initial draft were developed. Items are characterized by the cognitive domains of applying, analyzing, evaluating, and creating (Kelly, 2019). To analyze the feasibility of the developed items, it was administered to 50 students who took the same course. After correcting the papers, it was subjected to an item analysis. This analysis will aid in establishing the item difficulty, item discrimination, reliability,

and validity of the instrument. Analysis reveals 53 items to be retained and a Cronbach's alpha reliability coefficient of 0.91. This implies that the developed instrument has excellent reliability (George & Mallery, 2003). Meanwhile, these items were consulted with a panel of experts in Mathematics Education, Statistics, educational measurement, educational technology, and language to scrutinize the appropriateness of the developed items. After consolidating these results and recommendations, the final draft of the instrument was composed of 50 multiple-choice items.

Meanwhile, the second instrument was designed to capture students' perceptions of the role of collaborative GenAI in supporting their learning of data analysis, particularly about problem-solving, critical thinking, and written communication skills. Similar development and validation steps were followed as with the first instrument. However, the second instrument followed a Likert-scale format. A reliability coefficient of 0.95 indicates excellent internal consistency. Thus, this instrument was administered in digital format at the end of the course, following the completion of the post-test.

Lastly, learning materials for both teaching and assessment were appropriately developed with the integration of FOSS (Xu & Recker, 2022). It is important to note that these materials were developed by the researchers and compared with GenAI-generated counterparts to prevent students from being exposed to them before their interaction. More importantly, these materials were reviewed by the same panel of experts who evaluated the first research instruments to ensure content quality, alignment with learning objectives, and consistency with pedagogical standards. These materials are limited to slide presentations, individual tasks, and collaborative group tasks.

Tier 2. Quasi-Experimental Research Design

At this juncture of the study, all participating students received a comprehensive orientation and completed informed consent forms following ethical guidelines for conducting research of this nature. This was followed by the administration of a pre-assessment using a conventional approach to establish baseline performance. Notably, all groups were provided with identical learning materials, activities, and assessments utilizing a FOSS. The key differentiating factor in course delivery was the integration of a collaborative GenAI among the experimental groups. Specifically, Experimental Group 1 received an introductory session on prompt engineering before their immersion and interaction with the collaborative GenAI. The instructional phase spanned 6 weeks, during which students engaged with various data analytics tasks using FOSS. Upon completion of the learning period, all groups took a post-assessment and completed an exit survey. An overview of the study protocol is presented in Fig. 1.

Tier 3. Data Analysis

Appropriate data analysis techniques, such as frequency, mean, standard deviation, one-way analysis of covariance (ANCOVA), and one-way analysis of variance (ANOVA), were facilitated by using a licensed IBM SPSS version 28.

3 RESULTS

Effect of a collaborative GenAI on students' academic performance in data analysis

Table 2 presents the descriptive analysis of the scores obtained during the pre-assessment and post-assessment stages. The pre-assessment results indicate that students demonstrated a below-basic level of mastery in conducting data analysis using statistical software across the different groups. This signifies that none or very few of the participating students are familiar with using statistical software in conducting data analysis. While the post-assessment results show a change in the level of mastery among the participating students. Notably, the experimental groups became more competent in data analysis using statistical software with the aid of a collaborative GenAI. Further analysis using a one-way ANCOVA revealed a significant effect of groupings on post-assessment scores after controlling for pre-assessment scores, $F(2, 122) = 18.72$, $p < 0.001$, partial $\eta^2 = 0.235$, indicating a large effect size. While Bonferroni post hoc analysis uncovered that the Control Group scored significantly lower on the post-assessment than both Group 1 (M difference = − 6.27, SE = 1.03, p < 0.001, 95% CI [− 8.76, − 3.78]) and Group 2 (M difference = − 3.25, SE = 1.05, p = 0.008, 95% CI [− 5.81, − 0.69]). Additionally, Group 1 outperformed Group 2, with a significant difference in mean scores (M difference = 3.02, SE = 1.07, p = 0.016, 95% CI [0.44, 5.61]). Hence, it suggests that participation in Group 1 led to the highest performance on the post-assessment, followed by Group 2, with the Control Group performing the lowest. These results suggest that the integration of a collaborative GenAI in the instruction of data analysis using statistical software positively influences students' academic performance, likely by enhancing engagement, supporting individualized learning, and fostering collaborative problem-solving.

Table 2
Summary of Pre-Assessment and Post-Assessment

Group	**Pre-Assessment**			**Post-Assessment**		
	Mean	**Standard Deviation**	**Level of Mastery**	**Mean**	**Standard Deviation**	**Level of Mastery**
Control Group	15.64	3.35	Below Basic	39.02	6.74	Basic
Experimental Group 1	15.14	4.02	Below Basic	45.28	2.36	Advanced
Experimental Group 2	14.65	3.75	Below Basic	42.26	3.87	Proficient
Overall Statistic	**15.14**	**3.71**	**Below Basic**	**41.08**	**5.24**	**Proficient**
Statistical Limits: 45–50: Advanced ; 40–44 : Proficient; 35–39 : Basic; below 35 : Below Basic						

Perception towards the collaborative GenAI in the students' learning process

Table 3 presents the descriptive analysis of respondents' perceptions regarding the role of the collaborative GenAI in their learning experience throughout the course. The overall mean score of 3.55 with a standard deviation of 0.54 indicates that students strongly agreed that the collaborative GenAI

supported their learning journey in data analysis using statistical software. Items 1 to 12 focused on the perceived role of the collaborative GenAI on students' development of problem-solving, critical thinking, and written communication skills. All items in this category received a verbal interpretation of "strongly agree," suggesting that students felt more confident in their data analysis competencies as a result of engaging with the tool. Items 13 to 18, which pertain to the general use of GenAI in learning, yielded similarly strong results. It is worth noting that items 3, 10, and 16 received comparatively lower mean scores, indicating areas where students may require additional support. These findings highlight the need for enhanced instructional scaffolding, particularly during the planning-to-execution stages of problem-solving activities, to fully leverage the pedagogical potential of GenAI tools.

Performing a one-way ANOVA revealed a significant difference in the perceptions of the participating students toward the integration of GenAI in their data analytics course when grouped according to their respective instructional groups, $F(2, 115) = 3.36$, $p = 0.038$. This suggests that at least one of the groups differed significantly in their overall average scores. Tukey HSD test affirmed the significant mean difference between the Control Group and Experimental Group 1 ($M = -0.22$, $p = 0.031$, 95% CI [− 0.43, − 0.02]), indicating that Experimental Group 1 performed significantly better than the Control Group. The comparisons between the Control Group and Experimental Group 2 ($M = -0.08$, $p = 0.644$) and between Experimental Group 1 and Experimental Group 2 ($M = 0.15$, $p = 0.237$) were not statistically significant. These findings suggest that the intervention used with Experimental Group 1 had a meaningful effect on their outcomes compared to the Control Group. Still, Experimental Group 2 did not show a significant difference from either group. Nevertheless, these results contribute to understanding how the collaborative GenAI tool can foster higher-order thinking skills, particularly problem-solving, critical thinking, and written communication.

Table 3
Descriptive analysis of the survey

Items	Mean	Standard Deviation	Verbal Interpretation
1. I can identify the problem/s that need to be solved.	3.55	0.50	Strongly Agree
2. I can formulate a detailed plan to solve the problem/s.	3.52	0.55	Strongly Agree
3. I can implement the solution to the problem and monitor my progress effectively.	3.44	0.55	Strongly Agree
4. I can reflect upon and evaluate the process and outcomes of my solution to the problem.	3.59	0.52	Strongly Agree
5. I can identify the main issue or question in a problem that needs to be addressed.	3.57	0.52	Strongly Agree
6. I can examine the influence of context and assumptions on the problem.	3.56	0.53	Strongly Agree
7. I can analyze and evaluate the problem using relevant information and evidence.	3.56	0.53	Strongly Agree
8. I can formulate a well-reasoned conclusion or position on the solution to the problem.	3.52	0.50	Strongly Agree
9. I can consider the context and purpose when explaining a problem, ensuring it aligns with the assigned task.	3.60	0.55	Strongly Agree
10. I can use supporting evidence effectively to back up my explanations and solutions to problems.	3.51	0.58	Strongly Agree
11. I can organize and structure my explanations logically when writing about problems and solutions.	3.52	0.60	Strongly Agree
12. I can use proper language, terminology, and format when writing about problems and solutions.	3.52	0.58	Strongly Agree
13. I know how to incorporate generative AI into my learning activities.	3.64	0.48	Strongly Agree
14. I have the necessary digital skills to effectively utilize AI tools in my learning activities.	3.56	0.55	Strongly Agree
15. I am aware of the key learning strategies that should be used when applying AI tools to my learning activities.	3.60	0.49	Strongly Agree
16. I feel confident that I can overcome challenges that may arise when using AI technologies for my learning activities.	3.47	0.68	Strongly Agree
17. My current digital skills and understanding of my learning activities are sufficient to engage effectively	3.52	0.55	Strongly Agree
Statistical Limits: 1.00–1.74 : Strongly Disagree; 1.75–2.49 : Disagree; 2.50–3.24 : Agree; 3.25–4.00 : Strongly Agree			

Items	Mean	Standard Deviation	Verbal Interpretation
with AI for learning activities.			
18. The resources, tutorials, and support available to me have been effective in developing the skills needed to use AI for my learning activities.	3.67	0.47	Strongly Agree
Overall Statistic	**3.55**	**0.54**	**Strongly Agree**
Statistical Limits: 1.00–1.74 : Strongly Disagree; 1.75–2.49 : Disagree; 2.50–3.24 : Agree; 3.25–4.00 : Strongly Agree			

4 DISCUSSION

The findings of this study underscore the potential of integrating collaborative GenAI and FOSS to improve student learning outcomes in data analytics within the context of private HEIs in the Philippines. Notably, the analysis of pre- and post-assessment scores reveals a significant improvement in students' ability to perform data analysis using statistical software. The low pre-assessment scores reflect a general unfamiliarity with statistical tools, a trend consistent with Canlas (2019), who highlighted the continued reliance on traditional, lecture-based methods in Philippine statistics education. These conventional approaches often underutilize digital tools that could otherwise support the development of applied analytical skills. In contrast, the post-assessment results suggest that the integration of a collaborative GenAI contributed to measurable gains in student performance. These improvements may be attributed to the platform's ability to scaffold learning through real-time feedback, contextualized assistance, and support for complex problem-solving processes. Such affordances align with recent scholarship emphasizing the role of GenAI in developing students' competencies and skills in a particular discipline (Eith & Zawada, 2025; Megahed et al., 2024; Wu & Yu, 2023; Xu, 2024).

Meanwhile, the analysis of student perceptions regarding the integration of collaborative GenAI into the course indicates broadly positive learning experiences, particularly in areas requiring conceptual understanding, structured reasoning, and the articulation of thought processes. These findings highlight the potential of GenAI to transform students' roles from passive recipients of information to active constructors of knowledge. Through iterative dialogue and real-time feedback, GenAI tools enable students to reflect, question, and reframe their thinking throughout the learning process (Chan & Hu, 2023). However, items that received comparatively lower ratings seem to need more targeted instructional scaffolding during advanced phases of problem-solving and data analysis. This observation underscores the importance of designing learning environments that strike a balance between autonomous interaction with AI tools and structured, teacher-guided support. As Walkington and Bainbridge (2025) emphasize, effective GenAI integration requires not just technological adoption but pedagogical alignment to ensure that students are equipped to engage critically and competently with the tools available to them.

Moreover, the findings of this study contribute to the applicability and practical relevance of the SAMR model by illustrating how the integration of a collaborative GenAI platform can drive progressive transformation in teaching, learning, and assessment practices. At the substitution level, the collaborative GenAI was used to replicate traditional instructional tasks, such as retrieving definitions or procedural steps for statistical analyses. Even at this foundational stage, students were able to explore content independently, signaling an initial shift toward self-directed learning through looking for additional information, creating summaries, and conducting research. While in the augmentation level, the collaborative GenAI enhanced instructional delivery by providing immediate, personalized feedback and real-time clarification during both individual and collaborative tasks. Students could engage with the tool to test their understanding, clarify misconceptions, and receive AI-generated examples relevant to their coursework. In collaborative settings, students shared AI-generated content with peers, fostering deeper discussion and more effective knowledge exchange. Teachers, in turn, could validate these shared outputs, offer targeted guidance, and scaffold the learning process with greater precision and responsiveness. At the modification stage, the learning experience was substantially redesigned. Students began to leverage the collaborative GenAI not only as a source of information but as a tool for conducting data analysis, generating hypotheses, testing assumptions, and exploring complex problem-solving pathways. This marked a departure from traditional assessment models and allowed for more open-ended, analytical exploration in statistical learning. Finally, the redefinition level was exemplified by tasks that were previously inconceivable within a conventional classroom. Students co-constructed interpretations of statistical outputs, engaged in iterative dialogue with the GenAI tool to refine their thinking, and collaborated in real time with an intelligent learning partner to solve data-driven problems. These redefined activities reflect a profound pedagogical shift from static, instructor-led content delivery to dynamic, inquiry-based, and interactive learning experiences. Crucially, this transformation redefined the roles of both teachers and students, positioning the teacher as a facilitator and the student as an active participant in an AI-supported learning environment.

On one hand, this study reinforces the AI policy education framework proposed by Chan (2023). It supports pedagogical strategies that are not only effective but also ethical, inclusive, and aligned with future-readiness goals. The strong performance of students in Experimental Group 1 underscores the critical role of fostering artificial intelligence (AI) literacy and building both teacher and student capacity. This aligns with policy assertions by Ning et al. (2024), emphasizing that meaningful engagement with AI requires the development of new competencies across all educational stakeholders. Teaching students how to communicate effectively with GenAI is emerging as a foundational skill. Furthermore, the study highlights the ethical imperative of responsible AI integration in educational settings. The intentional design of scaffolded learning experiences, the structured deployment of the collaborative GenAI, and the commitment to ethical research practices such as informed consent collectively demonstrate how pedagogy can embody and uphold ethical standards in AI-enhanced education.

One notable limitation of this study lies in its focus on a single private HEI in the Philippines. This contextual specificity may limit the generalizability of the findings to other educational settings, such as public institutions or universities with varying levels of digital infrastructure and instructional capacity.

Furthermore, the relatively short duration of the intervention restricts the ability to observe long-term learning outcomes and sustained behavioral shifts in students' engagement with GenAI tools. Another limitation concerns the reliance on self-reported data, which may be subject to social desirability bias or overestimation of skill development. While the inclusion of pre- and post-assessment measures adds a degree of objectivity, these assessments may not fully capture the depth and breadth of learning transformations enabled by GenAI integration.

5 CONCLUSIONS & RECOMMENDATIONS

This study explored the integration of a collaborative GenAI in teaching data analytics within the context of a private HEI in the Philippines through a multi-tier system approach. The findings indicate that students who engaged with the collaborative GenAI demonstrated significantly improved academic performance and enhanced problem-solving, critical thinking, and written communication skills compared to peers in traditional instructional settings. The integration of collaborative GenAI not only deepened students' understanding of data analytics concepts but also fostered more positive attitudes toward learning with AI. These outcomes provide foundational evidence for the transformative potential of GenAI tools in data-intensive courses, especially when embedded within thoughtful instructional design. Nonetheless, the success of such innovation's hinges on careful pedagogical planning, adequate learner preparation, and equitable access to digital infrastructure.

Based on the findings and implications of this study, the following recommendations are proposed to guide the meaningful and responsible integration of GenAI tools in higher education:

1. Educators should adopt thoughtful and scaffolded instructional models that align GenAI tools with intended learning outcomes. Providing preparatory sessions on prompt engineering and AI literacy can maximize student engagement and deepen metacognitive learning;
2. Institutions must establish guidelines that ensure ethical, responsible, and equitable use of AI in classrooms;
3. GenAI tools should be used to facilitate peer-to-peer interaction, collaborative problem-solving, and real-time feedback loops. Structured collaboration enhances both technical competencies and communication skills;
4. HEIs could design and implement targeted faculty development initiatives focused on the pedagogical integration of GenAI tools;
5. Educational institutions and agencies could consider redesigning future curricula with the introduction of foundational competencies and skills in data literacy, AI integration, and responsible AI use;
6. To promote ethical and effective AI use in academic contexts, learning institutions should develop clear guidelines for the use of GenAI; and
7. Future studies should adopt longitudinal designs and expand to include diverse institutional types to assess better the sustained impact, scalability, and contextual adaptability of a collaborative GenAI-integrated instruction.

Declarations

The study was reviewed and approved by the iACADEMY Institutional Ethics Review Committee on April 3, 2025. All research procedures were conducted in accordance with the ethical standards of the institutional and national research committee, including adherence to the Philippine Data Privacy Act of 2012. Written informed consent was obtained from all participating students before data collection, and participants were assured of their right to withdraw from the study at any time without penalty.

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Author Contribution

J.S.P: Conceptualization, Methodology, Formal Analysis, Investigation, Data Curation, Writing - Original Draft. F.T.: Conceptualization, Software, Validation, Writing - Review & Editing.

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Data Availability

Data and other pertinent materials will be made available on reasonable request.

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Figures

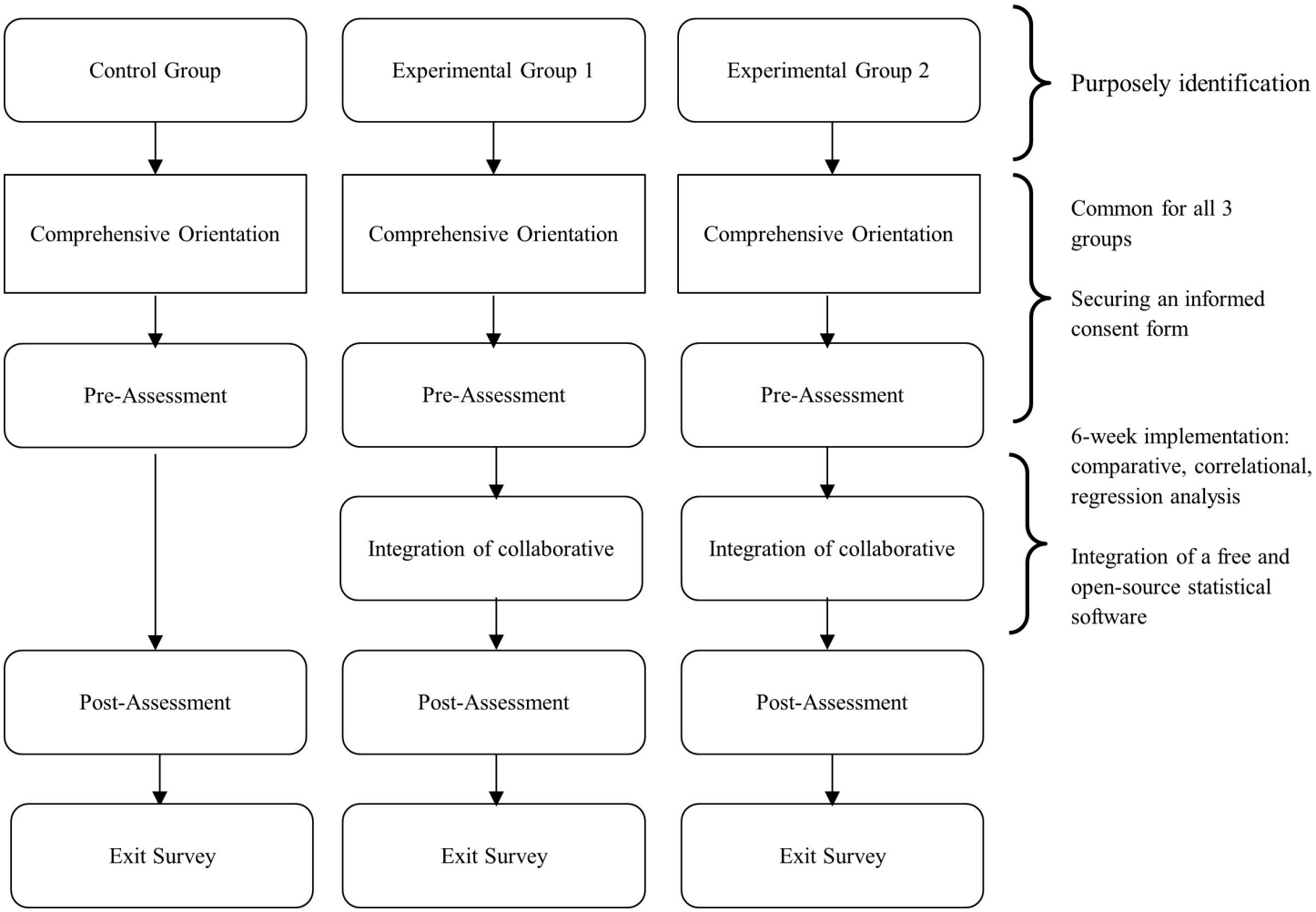

Figure 1

Study Protocol