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Exploring Implementations of GenAI in Teaching IS Subjects and Student Perceptions

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ABSTRACT

This research answers the call for Information Systems (IS) faculty to actively embrace rapidly advancing AI tools in teaching. We experimented with redesigning learning activities in two courses, requiring students to use GenAI, to aid student learning and teach responsible use of GenAI. The results show that students in the experimental group performed at the same or a higher level than those in the control group in terms of learning. Additionally, the two major concerns reported in prior research, (1) academic integrity and (2) student overreliance on AI and AI hallucinations, were not issues in our study. We conducted a student perception survey and found that students responded favorably to GenAI assignments, though not all students actively engaged with GenAI. This research demonstrates two ways of incorporating GenAI in teaching (assisting with writing a technical report and learning programming concepts) and provides initial empirical support for proactively adopting GenAI in higher education. Learning from the experiment, we provide practical recommendations for applying GenAI in teaching and learning IS subjects.

Keywords: Information systems education, Generative AI, Academic integrity, AI hallucination

1. INTRODUCTION

Generative Artificial Intelligence (GenAI), such as ChatGPT and Gemini, is capable of understanding human text, recognizing patterns, and engaging in human-like conversations, and is reshaping the business landscape and daily life. With the advance of GenAI technologies, GenAI skills are becoming one of the most in-demand skills sought by organizations (Mearian, 2024). A survey by Microsoft and LinkedIn found that 75% of knowledge workers are already using AI at work, 79% of leaders think that adopting AI is necessary to remain competitive, and 66% of leaders report that they would not hire someone who lacks AI skills (Microsoft, 2024). While a recent study has found that chatbots can provide informational and emotional support to employees and improve their performance (Lin et al., 2024), the societal impact of GenAI needs to be investigated further (Sabherwal & Grover, 2024).

In education, the recent breakthrough of GenAI models offers immense potential, such as reducing workloads for educators and providing personalized feedback for students. Students around the world are aware of the development of GenAI and are using various AI tools already (Abdelwahab et al., 2023; Chan & Hu, 2023; Farhi et al., 2023; Malik et al., 2023). In a survey of 1,000 higher education faculty and 1,600 college students, Shaw et al. (2023) found that about 50% of students and 22% of faculty used GenAI in Fall 2023, though 39% of faculty perceived that GenAI had a negative impact on student learning. Walczak and Cellary (2023) found that students use GenAI for many different school-related tasks, such as preparing for classes and exams, and completing homework and projects.

In response, many institutions discouraged or banned GenAI use due to concerns of academic integrity issues and GenAI errors (Sullivan et al., 2023). Educators worry that AI hallucination, where GenAI produces misleading, inaccurate, or false information that appears credible, could negatively affect student learning (Kutty et al., 2023). To effectively use GenAI for learning, students need to build sufficient domain knowledge and critical thinking skills to be able to differentiate between accurate and inaccurate information (Dahlkemper et al., 2023; Peres et al., 2023; Walczak & Cellary, 2023). Gradually, however, a growing number of universities, such as New York University, have developed policies that embrace GenAI as various disciplines may have found GenAI to be a useful tool that revolutionizes teaching and learning (Xiao et al., 2023). Out of the 132 universities that implemented an AI policy in Xiao et al.'s (2023) study, 43 banned and 89 embraced GenAI. Educators are actively assessing opportunities and challenges of and exploring effective responses to GenAI in higher education (Bansal et al., 2024; Denny et al., 2024; Dwivedi et al., 2023; Van Slyke et al., 2023). They agree that learning to use GenAI is a valuable skill that students should develop and master. This entails teaching students how to use GenAI to get desired outputs, how to critically assess generated results, and, most importantly, how to use GenAI ethically.

While researchers call for reassessment of current teaching practices to embrace AI tools (Dwivedi et al., 2023; Van Slyke et al., 2023), how to introduce GenAI in classrooms in higher education to capitalize on its benefits and manage its negative impacts is still an open research question. It is essential to understand the impacts of formally introducing GenAI to students through coursework, particularly regarding academic integrity and learning outcomes (Sullivan et al., 2023), as well as students' attitudes toward GenAI (Chan & Hu, 2023), since these factors significantly influence learning experiences.

In this study, we take the initiative to explore the following research questions. 1) How to introduce GenAI into learning activities in IS courses? 2) What are students' responses to the required use of GenAI in learning? 3) What are the impacts of GenAI use on academic integrity and mislearning caused by overreliance on AI and AI hallucination? We formally introduce GenAI into coursework, requiring students to use it for assigned tasks. This approach allows us to undertake two key tasks: incorporating GenAI elements in assignments to promote active learning and educate responsible use of GenAI. We demonstrate two ways of using GenAI to aid student learning, assisting with writing a technical report and learning programming concepts, and we assess learning outcomes and student responses to examine the impacts of GenAI use. Ultimately, this study presents practical implementations of GenAI in teaching and offers recommendations for integrating AI tools to aid student learning. Findings from the study aim to help educators understand students' perceptions of GenAI and reexamine the design and implementation of learning activities and assessments.

The remainder of the study is organized as follows. Section 2 presents a literature review that explores three main research streams on GenAI. In section 3, we discuss our research method, including details of assignment redesign. We present data analysis and results in section 4 and discussions and implications in section 5. Lastly, we discuss limitations and future research in section 6 and conclude the paper in section 7.

2. LITERATURE REVIEW

The recent development of GenAI initiates three major research streams regarding GenAI use in higher education: 1) understanding challenges and opportunities posed by GenAI, 2) understanding how students and educators perceive GenAI, and 3) how to use GenAI as a teaching tool.

2.1 Challenges and Opportunities

Research in this stream focuses on analyzing opportunities and challenges posed by GenAI in higher education. As summarized in Table 1, key issues identified are academic integrity, inaccurate and misleading information in GenAI outputs, and overreliance on AI.

Educators worry that students' use of GenAI makes it difficult to assess their learning, undermines their skill development, and leads to superficial learning or even mislearning. At the same time, researchers recognize various opportunities and possible benefits, such as enhancing student learning by providing fairly accurate information and explanations, offering personalized and instant feedback, and aiding them in writing and problem-solving tasks. Additionally, they value that AI tools can help reduce workload for teachers and administrators by replacing repetitive work, facilitating academic support and administrative tasks, and supporting teaching materials development and grading. Educators need to decide how to respond to the threats and opportunities posed by AI tools. In the IS field, Van Slyke et al. (2023) present four possible scenarios for the future: little to no impact, AI as automation tools, AI as a trusted augmentation partner, and AI as competition. They recommend that faculty should, in response, embrace AI tools as legitimate learning aids, become educated in GenAI, develop and incorporate AI-use policies, modify class activities and assessments, and educate students on AI use.

However, many of these articles are opinions or editorial (Dwivedi et al., 2023; Kakhki et al., 2024; Peres et al., 2023), literature review or overview (Adiguzel et al., 2023; Labadze et al., 2023; Sullivan e al., 2023; Van Slyke et al., 2023; Yu, 2024), or evaluations of GenAI capabilities (AlAfnan et al., 2023; Denny et al., 2024; Farrokhnia et al., 2024; Sobania et al., 2023) that do not actually implement GenAI in courses to investigate these issues or exploit possible opportunities. While educators and institutions are still in the process of assessing the impacts of GenAI, debating responses, and creating AI policies, what is missing is research that actually incorporates GenAI into classroom teaching to assess its impacts. We extend this stream of research by formally introducing students to GenAI in the classroom and requiring them to use GenAI to work on assignments. We demonstrate two ways of using GenAI to facilitate student learning of IS subjects, and we collect data on course assessments to evaluate GenAI benefits and concerns. Our study aims to provide practical recommendations on applying GenAI in teaching and learning IS subjects.

2.2 Student and Educator Perceptions

The second stream of research focuses on understanding students' and educators' perceptions of GenAI use in higher education. Researchers have conducted surveys worldwide, for example, Poland (Strzelecki, 2023; Walczak & Cellary, 2023), Netherlands (Abdelwahab et al., 2023), UAE (Farhi et al., 2023), Indonesia (Malik et al., 2023), China (Chan & Hu, 2023; Chan & Zhou, 2023), South Korea (Kim et al., 2020), India (Raman et al., 2023), Ghana (Bonsu & Baffour-Koduah, 2023), and USA (Shaw et al., 2023). These studies found that most students are comfortable using and have been using GenAI tools. Students think GenAI is helpful in providing personalized feedback (Bonsu & Baffour-Koduah, 2023; Chan & Hu, 2023), supporting writing (Farhi et al., 2023; Malik et al., 2023), programming (Walczak & Cellary, 2023), language learning (Malik et al., 2023), and exam preparation tasks (Walczak & Cellary, 2023), and improving critical thinking and problem-solving skills (Farhi et al., 2023; Walczak & Cellary, 2023). At the same time, those survey studies found that participants are concerned about inaccuracy, biases, insensitivity, and out-of-context information in AI outputs, and they worry about unethical use, overreliance on GenAI, security, and limiting human interactions. Overall, findings from these surveys correspond to the benefits and concerns identified in the first stream of research.

Additionally, researchers are beginning to investigate factors affecting user adoption of GenAI. Guided by the expectancy value theory (EVT), Chan and Zhou (2023) found that the intention to use GenAI is positively correlated with perceived value and knowledge of GenAI but negatively correlated with perceived cost. They suggested that students might use GenAI more if institutions educate them on the potential value of GenAI, enhance their GenAI literacy, and help mitigate concerns associated with GenAI. Several studies (Al-Abdullatif, 2023; Kim et al., 2020; Lai et al., 2023;

Concepts	Articles
Challenges, Weaknesses, & Concerns	
Academic integrity issues	Adiguzel et al., 2023; Denny et al., 2024; Dwivedi et al., 2023; Farrokhnia et al., 2024; Kakhki et al., 2024; Labadze et al., 2023; Sullivan et al., 2023; Van Slyke et al., 2023; Yu, 2024
Inaccurate and misleading information (hallucinations) in GenAI outputs	Adiguzel et al., 2023; Denny et al., 2024; Labadze et al., 2023; Peres et al., 2023; Sobania et al., 2023; Sullivan et al., 2023
Undermine learning process, superficial learning	AlAfnan et al., 2023; Dwivedi et al., 2023; Sullivan et al., 2023; Yu, 2024
Over-dependence on AI	Adiguzel et al., 2023; Denny et al., 2024; Yu, 2024
Negative impact on skill development	Dwivedi et al., 2023; Farrokhnia et al., 2024; Kakhki et al., 2024; Van Slyke et al., 2023; Yu, 2024
Privacy	Adiguzel et al., 2023; Dwivedi et al., 2023; Labadze et al., 2023
Security	Dwivedi et al., 2023; Labadze et al., 2023
Make assessment of learning difficult	AlAfnan et al., 2023; Denny et al., 2024; Farrokhnia et al., 2024; Labadze et al., 2023
Train students to use GenAI responsibly, need to retrain faculty	Labadze et al., 2023; Peres et al., 2023; Van Slyke et al., 2023
Opportunities, Strengths, & Benefits	
Personalized learning and real-time responses, self-directed learning, virtual tutor, interactive learning environments	Adiguzel et al., 2023; Farrokhnia et al., 2024; Kakhki et al., 2024; Labadze et al., 2023; Sobania et al., 2023; Sullivan et al., 2023; Van Slyke et al., 2023; Yu, 2024
Provide fairly accurate information	AlAfnan et al., 2023; Sobania et al., 2023; Sullivan et al., 2023
Support learning for complex tasks (e.g., critical thinking, writing), improve writing and problem-solving skills	AlAfnan et al., 2023; Farrokhnia et al., 2024; Labadze et al., 2023; Peres et al., 2023; Sullivan et al., 2023
Provide information, explanations, exemplary solutions	Denny et al., 2024; Farrokhnia et al., 2024; Kakhki et al., 2024; Sobania et al., 2023
Increase student motivation, improve academic performance	Adiguzel et al., 2023; Kakhki et al., 2024
Reduce workload of educators, administrators, and management	Dwivedi et al., 2023; Farrokhnia et al., 2024; Labadze et al., 2023; Peres et al., 2023; Van Slyke et al., 2023; Yu, 2024
Support educators in developing teaching materials, exercises, and assignments	AlAfnan et al., 2023; Denny et al., 2024; Dwivedi et al., 2023; Kakhki, et al., 2024; Labadze et al., 2023; Peres et al., 2023; Van Slyke et al., 2023; Yu, 2024

Table 1. Summary of Literature on GenAI Challenges and Opportunities

Maheshwari, 2024) have applied the Technology Acceptance Model (TAM) to study the relationship between students' perceptions and their AI adoption intention: each of these studies has included similar constructs but applied a variation of the TAM model. A common finding of these studies is that perceived usefulness is positively associated with users' adoption intention.

One common issue is that students involved in these studies are not formally introduced to GenAI through coursework. Thus, while some students may have experience using GenAI, others may not. We extend this stream of research by collecting and analyzing perception data after students have actually used GenAI to complete coursework in a guided environment. Our study design enables us to assess students' general perceptions on limitations, values, and adoption of GenAI and specific perceptions on the effectiveness of GenAI on particular learning tasks. We also expand survey questions, assessing students' preferences for different learning tools. Our study helps educators better understand students' awareness and attitudes toward GenAI.

2.3 Effective Use of GenAI for Teaching

Researchers have started experimenting and testing various ways of using GenAI to support learning, for example, addressing theory- and application-based course-related questions (AlAfnan et al., 2023), assisting writing tasks (Halaweh, 2023; Hsiao et al., 2023; Mollick & Mollick, 2022), learning coding and design science research (Denny et al., 2024; Hartley et al., 2024; Memmert et al., 2023), and training students to develop higher-level thinking such as applying knowledge to a new context, explaining different aspects of concepts, and evaluating options (Hsiao et al. 2023; Mollick & Mollick, 2022). Guided by the self-regulated learning (SRL) and judgment of learning frameworks, Chang et al. (2023) proposed a conceptual model and provided examples to help educators implement chatbots in the classroom. While these studies identified positives and limitations of GenAI and provided implementation recommendations, the proposed approaches were assessed by researchers, not tested by students. A few studies have experimented with letting students use a custom-chatbot to teach AI concepts (Chen et al., 2023), learn programming (Essel et al., 2022), and assist with course review (Lee et al., 2022), or use ChatGPT (Dahlkemper et al., 2023; Essien et al., 2024; Zhong & Kim, 2024) for learning tasks, and they found positive effects on student learning. More empirical studies that implement GenAI in teaching are needed to further examine GenAI impacts on student data, especially on the issues of academic integrity and mislearning.

Recent studies indicate the need for higher education to proactively adopt GenAI in teaching and for instructors to guide students to appropriately and ethically use GenAI. Researchers emphasize that it is critical for students to have sufficient knowledge and skills so that they are capable of evaluating GenAI outputs for accuracy to minimize the impact of AI hallucinations and thus mislearning (Bull & Kharrufa, 2024; Dahlkemper et al., 2023; Hartley et al., 2024). We contribute to this stream of work by taking steps to incorporate GenAI elements into IS courses and assessing the associated impacts on student learning, academic integrity, and mislearning caused by GenAI hallucinations.

In summary, AI-in-education literature has found that AI could have both positive and negative impacts on students' learning outcomes. If instructors find effective ways to incorporate GenAI under a teacher-controlled environment, they can materialize its benefits and reduce its negative aspects. Once students learn the pros, cons, and values of GenAI, they can use GenAI more responsibly, which could (1) improve learning outcomes, (2) reduce academic integrity issues, and (3) encourage more use of GenAI as an effective learning tool. In this study, we demonstrate two ways of incorporating GenAI into class activities and examine its impacts on the above three. Based on the results of the study, we identify practical implications for the effective implementation of GenAI in teaching and learning.

3. RESEARCH METHOD

We adopted a quasi-experimental research design in two undergraduate-level IS courses in a public university in the United States to examine the impact of incorporating GenAI in learning activities on student learning outcomes and academic integrity issues. The College of Business offers both courses, Introductory Business Programming and Database Concepts and Administration, twice a year. Each course has been taught by the same instructor for over 10 years. We chose the Fall 2023 sections as the experimental group and the Fall 2022 sections as the control group and conducted between-group analyses of student performances on a set of assignments. Both groups were taught in a face-to-face mode.

For the experimental group, instructors formally introduced GenAI tools, ChatGPT in particular, and redesigned some assignments, requiring students to use a GenAI tool to complete them. The control group completed the same set of assignments without the GenAI elements. We selected Fall 2022 sections as the control group because ChatGPT was first released to the public on November 30, 2022, one week before the end of the semester, and after students had completed the assignments. Since other popular GenAI tools such as Google's Gemini (formally known as Bard) and Microsoft's Copilot were unveiled a few weeks later, ChatGPT equivalent GenAI tools were basically unavailable to the control group. In this research design, the only instructional differences between the two groups are the inclusion of GenAI elements and the availability of GenAI tools for the experimental group.

3.1 Assignment Redesigns

Conducting research and writing technical reports is a type of assignment commonly used to help students develop a deeper understanding of concepts and acquire problem-solving and critical thinking skills (Bean & Melzer, 2021). As part of the IS program-level student learning outcome (SLO) assessment, both courses require students to complete a report writing assignment. For the experimental group, instructors redesigned this assignment and a coding assignment for the programming course, incorporating GenAI elements. These assignments were introduced in the middle to the second half of the semester, after students had acquired basic subject knowledge.

3.1.1 Redesign of Writing Assignments. In the database course, students write a report that assesses three database technologies, SQL, NoSQL, and NewSQL, with the goal of helping IT professionals select the proper database technologies. In the programming course, students write a report assessing the Python language with the goal of helping IT professionals make adoption decisions. Report requirements and evaluation criteria are the same for both groups.

Instructors of the two courses collaborated to redesign the writing assignments for the experimental group, adding GenAI elements. While the topic and scope of the assignment were the same, the experimental group completed the assignment in two steps. First, instructors introduced GenAI tools, requiring students to use it to create a one-page AI-generated draft on the assigned topic. This process involved selecting a GenAI app and experimenting with prompts. Students were then tasked with critically evaluating the AI-generated draft, assessing its strengths and weaknesses, which are provided as part of the assignment instructions. In the second step, students were tasked to conduct independent research to verify the points made by GenAI, source credible information to revise and enhance the draft, and document their revision process using Microsoft Word's track changes feature.

This assignment redesign is based on similar techniques recommended in literature (AlAfnan et al., 2023; Hsiao et al., 2023; Mollick & Mollick, 2022). By allowing students to generate and revise an AI draft, this approach helps them start the writing process easily with relevant ideas. It formally introduces students to GenAI tools, provides an opportunity for them to learn ethical use of GenAI in learning, and helps students understand the strengths and weaknesses of GenAI through their interaction with GenAI.

3.1.2 Redesign of Coding Assignment. One of the key elements for mastering objected-oriented programming languages is understanding the concept of classes and how to use them. Students often struggle with this topic due to its abstract nature. In this Python programming course, one team-based assignment requires students to develop code, modeled after a Loan class in a banking application with specific requirements, to demonstrate how to create and use the class object. A sample code file with numerous conceptual and syntax errors is provided. Students are required to document each error in the sample code, explain why it is wrong, and provide the correct code in a text file that meets the specified requirements. This type of learning activity is proven effective to teach basic programming (Sandoval-Medina et al., 2024). While the requirements and evaluation criteria are the same for both groups, the instructor added a GenAI element for the experimental group. After students spent 30 minutes creating their own coding error documentation, they were instructed to use ChatGPT or other GenAI apps to help them identify and correct coding errors in the sample file. Then, students were instructed to evaluate AI output and compare it with their own analysis and were permitted to incorporate AI outputs in their coding error documentation. This redesign lets students use GenAI as a learning tool as proposed in Mollick and Mollick (2022). It helps students practice an effective and ethical way of learning coding with GenAI while teaching them to assess AI outputs instead of blindly accepting them.

3.2 Survey Instrument

We developed an online survey to learn students' responses to the redesigned assignments and their perceptions of GenAI. The well-established TAM framework proposes that users' perceived usefulness of a technology is a key determinant of their adoption of the technology (Davis, 1989). The related EVT also links perceived value and expectancy to users' decisions to engage in a task (Wigfield & Eccles, 2000). While we do not intend to formally investigate factors affecting students' AI adoption or engagement, we are interested to learn students' attitudes toward AI adoption in learning, their knowledge of GenAI, and their perceptions of the usefulness of AI, especially, whether they think the AI assignments help them learn course subjects. Previous studies on students' AI perceptions often include questions centered on students' knowledge and perceived values of GenAI and adoption intention (Chan & Hu, 2023; Chan & Zhou, 2023; Essel et al., 2022; Lee et al., 2022; Malik et al., 2023). Perceived usefulness or value construct is also used in studies that formally model students' AI use or adoption intention under the TAM framework (Al-Abdullatif, 2023; Kim et al., 2020; Lai et al., 2023; Maheshwari, 2024). We adapted and expanded survey items from these studies and developed additional items assessing students' responses to the redesigned assignments and their preferences on learning tools, guided by the TAM and EVT research. For example, we adapted utilities and attainment values items from Chan and Zhou (2023), which use the EVT framework, and we added new items (Q16, Q18, Q19, and Q20) to gauge students' responses to the use of GenAI in the redesigned assignments. Items Q24-Q27 were developed to measure students' preferences between GenAI and other learning tools. A five-point Likert scale was used, with 1 for "strongly disagree" and 5 for "strongly agree." We also included two questions (Q1-Q2) measuring students' AI use frequency before and during the experimental semester, using a five-point Likert scale (1=never to 5=always). The full question list is presented in the Appendix.

3.3 Data Collection

Since the only instructional difference was the introduction of GenAI to the experimental group alongside the redesigned AI-enabled assignments, we collected relevant performance data to analyze the impact of GenAI elements on student learning and academic integrity.

For the report assignments, we collected students' grades and Turnitin similarity scores for both groups. For the experimental groups, we also collected Turnitin AI scores, measured as the percentage of text possibly generated by AI. We further submitted reports to ZeroGPT to collect additional AI detection scores. We chose ZeroGPT because it offers a free version of AI detecting service and is found to be a reliable AI detector (Bellini et al., 2024; Walters, 2023).

The database course includes a set of multiple-choice questions related to the report assignment in the proctored final exam. We collected student data on these questions to assess the impact of GenAI on learning. For the programming course, other than the redesigned coding assignment, we also collected scores of two individual coding assignments and two individual exams (a quiz and final exam), which were given after the redesigned assignment. The coding assignments required students to develop code for specific tasks, applying object-oriented programming. Both exams were proctored. The quiz assessed students' understanding of function- and class-related subjects, and the final exam was comprehensive. Both used a multiple-choice question format and included code interpretation, analysis, and error identification questions to assess students' understanding of coding concepts, rules, and applications. The final exam also required students to write code to demonstrate mastery of object-oriented programming.

In addition to students' assessment data, we collected background survey data for both groups in both courses at the beginning of the semesters. To learn how students responded to the redesigned assignments and their perceptions of GenAI, we collected GenAI survey data from the experimental group at the end of the semester. The database and programming courses had 38 and 22 students in the control group, and 36 and 37 students in the experimental group, respectively. While each group included some students who enrolled in both courses, none of the students were included in both groups.

4. DATA ANALYSIS AND RESULTS

For the database course, a database knowledge survey was administered at the beginning of both semesters. Students reported their knowledge levels on 21 questions in a 5-point Likert scale (0 for no knowledge and 4 for extensive knowledge). The mean knowledge level for the experimental group (0.63) was lower than that of the control group (0.87). The difference, -0.25, was weakly significant, $t(65)=-1.548$, $p=0.063$. Thus, at the beginning of the semesters, both groups had "limited" to "no knowledge" on general database subjects.

For the programming course, students self-reported their GPAs and programming experience at the beginning of both semesters. GPA was measured using a five-point Likert scale, with 5 for 3.71-4.0 and 1 for <=2.3. Programming experience was measured using a five-point Likert scale, with 5 for expert and 1 for no experience. The mean GPA for the experimental group (3.3) was higher than that of the control group (3.24). However, the difference, 0.06, was not significant, $t(56)=0.18$, $p=0.86$. The mean programming experience for the experimental group (1.68) was lower than that of the control group (1.81). The difference, -0.13, was not significant, $t(56)=-0.57$, $p=0.57$. Thus, both groups had similar academic standing and "little" to "no programming experience" at the beginning of the semesters.

Since GenAI elements and tools were only available to the experimental group, a between-group comparison of student performance on assessments could be used to evaluate the impact of using GenAI on learning. Because not all students completed all the collected assessments, the analysis was based on available data for both courses and groups.

4.1 Learning Analysis

The points used in each assessment are as follows. The total score is nine for the database report and four for the Python report. For the database course, the final exam included 13 questions related to database comparison criteria that students could have used in their reports. Students' scores on these questions were collected from both groups, with 1 point for each question. For the Python course, the total score for the assignments and the quiz is two points each, and it is 24 for the exam. Table 2 presents descriptive statistics of the collected assessments for both courses.

For all the assessments, the mean scores of the experimental group were higher than those of the control group in both courses. We further conducted a series of independent sample t-tests to compare differences of the means between the two groups to evaluate the impact of using GenAI to learn course subjects. Levene's test of homogeneity of variance (Levene, 1960) was used to select the correct type of test, either two-sample t-test of equal variance or unequal variance. We also performed bias-corrected and accelerated (BCa) bootstrap robust tests on the data (Efron & Tibshirani, 1993). Table 3 summarizes the test results at a 95% confidence interval level.

For the database course, students of the experimental group scored higher (mean=8.43) than the control group (mean=7.78) on the assessed questions, and they also scored slightly higher on the report assignment. However, these differences were not significant ($p>0.1$). For the programming course, the mean Assignment 1 score for the experimental group (1.85) was higher than that of the control group (1.67). The difference, 0.18, was significant, $t(54)=2.59$, $p=0.012$, representing a moderate to large effect size of $d=0.72$ (Cohen, 1988). Similarly, the mean Assignment 2 score for the experimental group (1.86) was higher than that of the control group (1.60). The difference, 0.25, was significant, $t(27.42)=2.13$, $p=0.042$, representing a moderate to large effect size of $d=0.68$. The differences in the report, quiz, and exam were not significant ($p>0.1$). The bootstrap confidence intervals for the corresponding tests confirmed our conclusions. Thus, students of the experimental group learned the course subjects at the same or higher level than students of the control group in our study.

4.2 Academic Integrity Analysis

To check for academic integrity issues, we analyzed the similarity and AI-written percentage scores generated by Turnitin (AlAfnan et al., 2023; Halaweh, 2023). Table 4 presents the descriptive statistics and test results. All similarity scores were below the maximum threshold set for this assignment, 40%, above which would invoke a penalty for academic dishonesty conduct. We further conducted independent sample t-tests to compare the means between the two groups.

For the database course, the mean similarity index score (15.53) for the experimental group was higher than that of the control group (10.58). The difference, 4.95, was only weakly significant, $t(66)=1.98$, $p=0.051$. This higher difference was partially because the AI draft of the experimental group was submitted to Turnitin during the first phase such that it was included in the paper repository for similarity analysis for the final report. For the Python course, the mean similarity score (9.6) for the experimental group was higher than that of the control group (7.2). The difference, 2.4, was not significant, $t(48)=1.18$, $p=0.246$. The bootstrap confidence intervals for the corresponding tests confirmed our conclusions. Thus, the experimental group's similarity scores were comparable to those of the control group.

Using AI detection tools is a viable solution for instructors to assess whether students have used GenAI to write their reports, even though such tools may not be robust for AI paraphrasers (Baron, 2024). The mean AI written scores for both courses (12.27 and 7.1) were low, and so were the scores at the 3rd quartile, considering that the initial drafts were 100% AI-written. Shaw et al. (2023) found that the average acceptable AI written score is 35% among AI-using faculty. In our study, 96.7% of students (all but two out of 60) scored below this threshold, suggesting no prevalence of integrity issues.

Since AI detection scores are irrelevant for the control group, we collected extra data to assess the potential academic integrity issue involving AI. While we did not introduce GenAI or give students permission to use GenAI in Spring 2023, we suspected that some students might have used GenAI to complete the reports, given the public availability of GenAI tools. As a robust analysis, we compared the report data for Spring 2023 with that of the experimental group as shown in Table 5.

There were no significant differences between these two semesters in terms of report grades and AI matching scores by both AI detecting programs. The only significant difference was the similarity score of the database course, and it could be due to the AI-draft submission requirement for the experimental group. The mean AI written percentage generated by ZeroGPT was higher for Spring 2023 than Fall 2023 for both courses. While Turnitin detected a higher AI written percentage in Spring 2023 than Fall 2023 in the programming course, the opposite was observed in the database course. During the Spring 2023 semester, when the assignment instructions and the university did not have any explicit rule about GenAI, a higher average AI written percentage was observed in three out of the four measures. Further inspection of AI detection scores showed that, during the Spring 2023 semester, most students did not use AI when writing the report, but some used GenAI without permission.

4.3 Student AI Survey Analysis

For the AI survey, eight students enrolled in both courses, and we only included their first responses, resulting in 65 responses in the analysis. Most of the participants were seniors (72.3%) and juniors (23.1%) of the IS program. Table 6 presents the survey data.

One purpose of redesigning assignments was to encourage students to use GenAI in their learning. We compared responses to Q1 and Q2 and found that AI usage frequency increased at the end of the semester with a mean of 3.2 ("sometimes") vs. the before-the-semester mean of 2.55 ("rarely"). A paired-sample t-test on usage frequency showed that this increase is significant ($t=4.279$, $p<0.001$). Because completing redesigned assignments mandated GenAI use one to two times, i.e., "rarely" level, we expected the number of participants who have never used GenAI to decrease, as indicated in the data (24.6% to 1.5%). During the experimented semester, 78.5% of participants had used GenAI from "sometimes" to "always" vs. only 55.4% before the semester, thus this 23.1% increase indicates the increased use of GenAI by students. However, the same percentage of participants (20%, though not likely the same students) still rarely used GenAI, indicating that some students may have reservations about or a lack of interest in using GenAI.

Courses	Measures	Groups	N	Mean	Median	SD	Variance	Min	Max	1st quartile	3rd quartile
Database	Report	Exp	30	7.33	7.55	1.25	1.57	4.70	9.00	6.48	8.33
		Control	38	7.30	7.38	0.77	0.59	5.58	9.00	7.02	7.79
	Exam	Exp	30	8.43	9.00	2.76	7.63	3.00	13.00	6.75	10.25
		Control	37	7.78	8.00	2.92	8.51	3.00	13.00	5.00	10.00
Python	Report	Exp	30	3.63	3.70	0.32	0.10	2.75	4.00	3.49	3.85
		Control	20	3.61	3.63	0.30	0.09	2.55	4.00	3.51	3.75
	Assignment1	Exp	35	1.85	2.00	0.23	0.05	1.10	2.00	1.80	2.00
		Control	21	1.67	1.70	0.28	0.08	1.00	2.00	1.50	1.90
	Assignment2	Exp	29	1.86	2.00	0.27	0.07	0.80	2.00	1.85	2.00
		Control	20	1.60	1.80	0.48	0.23	0.50	2.00	1.26	2.00
	Quiz	Exp	35	1.54	1.55	0.23	0.05	0.90	1.90	1.40	1.70
		Control	21	1.49	1.50	0.25	0.06	0.90	1.90	1.38	1.63
	Exam	Exp	37	16.56	16.65	3.96	15.70	8.35	22.15	14.00	19.70
		Control	22	15.29	13.80	3.38	11.44	10.85	22.15	12.71	18.06

Table 2. Descriptive Statistics of Course Assessments

Courses	Measures	Mean Diff	df	t	p	Cohen's d	BCa 95% CI	
							Lower	Upper
Database	Report	0.03	45.76	0.10	0.922	0.03	-0.50	0.54
	Exam	0.65	65.00	0.93	0.178	0.23	-0.79	1.94
Python	Report	0.02	48.00	0.25	0.803	0.07	-0.15	0.20
	Assignment1	0.18	54.00	2.59	0.012**	0.72	0.03	0.33
	Assignment2	0.25	27.42	2.13	0.042**	0.68	0.02	0.48
	Quiz	0.05	54.00	0.79	0.433	0.22	-0.07	0.19
	Exam	1.27	57.00	1.25	0.215	0.34	-0.63	3.01
***p*<0.05								

Table 3. Between Group Comparisons of Means of Course Assessments

Courses	Measures	Groups	N	Min	1st quartile	Median	3rd quartile	Max	Mean	SD	Mean Diff	df	t	p
Database	Similarity	Exp	30	2	6.75	14.00	22.50	40	15.53	10.25	4.95	66	1.98	0.051
		Control	38	0	3.00	7.00	16.25	38	10.58	10.21				
	Turnitin AI	Exp	30	0	0.00	6.00	18.75	62	12.27	16.60				
Python	Similarity	Exp	30	2	3.75	8.50	13.75	36	9.60	7.26	2.40	48	1.18	0.246
		Control	20	0	1.50	6.50	10.75	27	7.20	6.78				
	Turnitin AI	Exp	30	0	0.00	0.00	14.00	34	7.10	10.01				

Table 4. Statistics of Report Assignments on Similarity and AI Detection

		Fall2023			Spring2023			Fall 2023 vs Spring 2023				
Courses	Measures	N	Mean	SD	N	Mean	SD	Mean Dif	d	t	p	Cohen's d
Database	Score	30	7.33	1.25	34	7.18	0.90	0.15	62	0.56	0.577	0.14
	ZeroGPT	30	11.40	17.32	34	17.08	24.96	-5.68	62	-1.04	0.300	-0.26
	Turnitin AI	30	12.27	16.60	34	7.53	20.08	4.74	62	1.02	0.311	0.26
	Similarity	30	15.53	10.25	34	5.79	4.62	9.74	39	4.79	0.000***	1.25
Python	Score	30	3.63	0.32	18	3.72	0.24	-0.09	46	-1.04	0.304	-0.31
	ZeroGPT	30	12.89	13.72	18	19.45	29.18	-6.56	21.59	-0.90	0.380	-0.32
	Turnitin AI	30	7.10	10.01	18	14.06	31.70	-6.96	19.05	-0.90	0.377	-0.33
	Similarity	30	9.60	7.26	18	6.22	5.91	3.38	46	1.67	0.102	0.50
****p*<0.01												

Table 5. Comparison of the Report Assignments Between Fall and Spring 2023

Category	Questions			Survey Distribution				
		Mean	SD	1	2	3	4	5
Usage	Q1	2.55	1.16	24.6%	20.0%	35.4%	15.4%	4.6%
	Q2	3.20	0.89	1.5%	20.0%	41.5%	30.8%	6.2%
Knowledge of GenAI	Q3	3.98	0.87	0.0%	7.7%	15.4%	47.7%	29.2%
	Q4	3.66	0.99	0.0%	15.4%	24.6%	38.5%	21.5%
	Q5	3.89	0.89	1.5%	6.2%	16.9%	52.3%	23.1%
	Q6	3.88	0.88	0.0%	9.2%	16.9%	50.8%	23.1%
	Q7	3.78	1.07	1.5%	10.8%	27.7%	27.7%	32.3%
	Q8	3.82	1.20	6.2%	9.2%	16.9%	32.3%	35.4%
	Q9	3.63	1.01	1.5%	13.8%	24.6%	40.0%	20.0%
Utility value	Q10	4.34	0.73	0.0%	1.5%	10.8%	40.0%	47.7%
	Q11	4.02	0.87	0.0%	9.2%	9.2%	52.3%	29.2%
	Q12	3.98	0.76	1.5%	1.5%	15.4%	60.0%	21.5%
	Q13	4.29	0.74	0.0%	1.5%	12.3%	41.5%	44.6%
Attainment value	Q14	3.89	0.77	1.5%	3.1%	16.9%	61.5%	16.9%
	Q15	4.02	0.87	1.5%	4.6%	13.8%	50.8%	29.2%
	Q16	3.88	0.94	1.5%	7.7%	18.5%	46.2%	26.2%
	Q17	3.02	1.19	10.8%	26.2%	24.6%	27.7%	10.8%
	Q18	3.35	1.02	6.2%	10.8%	35.4%	36.9%	10.8%
	Q19	3.29	1.07	4.6%	20.0%	29.2%	33.8%	12.3%
	Q20 (p)	4.00	0.71	0.0%	0.0%	24.3%	51.4%	24.3%
Adoption intention	Q21	3.66	0.97	1.5%	9.2%	32.3%	35.4%	21.5%
	Q22	3.72	1.10	3.1%	10.8%	26.2%	30.8%	29.2%
	Q23	3.78	1.05	4.6%	6.2%	21.5%	41.5%	26.2%
Preference of learning tool	Q24	3.51	1.09	4.6%	12.3%	30.8%	32.3%	20.0%
	Q25	3.42	0.97	3.1%	10.8%	41.5%	30.8%	13.8%
	Q26 (p)	3.23	1.20	7.7%	20.0%	32.3%	21.5%	18.5%
	Q27	2.76	1.04	10.8%	29.7%	37.8%	16.2%	5.4%
(p) Q20 and Q26 are only for the programming course.								

Table 6. Summary Statistics of GenAI Survey

Category	No of Items	Mean	Variance	SD	Cronbach's Alpha
Knowledge	7	26.65	21.013	4.584	0.784
Perceived value	10	38.08	36.603	6.050	0.859
Attainment value	6 *	21.45	18.907	4.348	0.828
Utility value	4	16.63	6.080	2.466	0.799
Adoption intention	3	11.17	6.768	2.601	0.778
Preference (r)	3 *	7.85	7.226	2.688	0.762
* Q20 and Q26 are not included as they are only for the programming course.					

Table 7. Cronbach Alpha Coefficient Results (N=65)

Overall, students were aware of the limitations and proper use of Gen AI, with means ranging from 3.63 to 3.98 for Q3 to Q9. These seven items represent knowledge of GenAI, with a mean score of 3.81, indicating that students had a good understanding of GenAI. Specifically, they were aware that GenAI can produce factually inaccurate outputs (mean=3.98, SD=0.87). The lowest mean score was for Q9 regarding the potential copyright violation of output produced by GenAI.

Students perceived positive values of GenAI, with an average value of 3.81 for the ten items (Q10 to Q19). They perceived higher utility values (mean=4.16) than attainment values (mean=3.58) when using GenAI. The highest mean score was for AI's value in saving time (Q10, mean=4.34, SD=0.73), followed by its 24/7 availability (Q13, mean=4.29, SD=0.74). The highest attainment value was for improving understanding of course subjects (Q15, mean=4.02, SD=0.87), and the lowest was for GenAI's value in improving writing skill (Q17, mean=3.02, SD=1.19). Students of the programming course perceived high value of GenAI in improving their understanding of coding concepts (Q20, mean=4.0, SD=0.71), indicating that the students valued GenAI differently depending on the learning tasks.

Students had an overall positive view on AI adoption, with a mean of 3.72 on the adoption item group (Q21 to Q23). They expressed a favorable attitude towards integrating GenAI in their learning practices (Q23, mean=3.78, SD=1.05). However, students slightly favored other learning supports, such as search engines or online videos over GenAI for learning course subjects (Q25, mean=3.42, SD=0.97; Q26, mean=3.23, SD=1.20) and completing writing assignments (Q24, mean=3.51, SD=1.09). Interestingly, they were not in favor of using search engines for coding assignments (Q27, mean=2.76, SD=1.04).

Cronbach's alpha values for the GenAI knowledge, value, adoption intention, and preference scales are 0.784, 0.859, 0.828, and 0.762, respectively (all greater than 0.7, see Table 7), indicating internal consistency (Kline, 1993). We present the reversed scales (r) of preference items such that a high value indicates a preference to use GenAI over other tools. We found that the Cronbach's alpha values of our knowledge and value constructs are comparable to the values 0.812 and 0.876 found in Chan and Zhou (2023).

5. DISCUSSION AND IMPLICATIONS

5.1 Discussion of GenAI Use in Assignments

Previous studies have identified two main concerns of GenAI in education: academic integrity issues and mislearning caused by GenAI hallucinations. We analyzed whether these perceived concerns by educators could be serious issues that negate the possible benefits of GenAI.

For a research report that is written based on evidence from credible sources, a certain percentage of similarity is expected, and 25% similarity, displayed in green color in Turnitin, should be considered as no academic integrity issue. Six out of 60 students in the experimental group vs. four out of 58 in the control group received a higher than 25% similarity score, while all similarity scores were within 40%. Overall, the similarity scores were comparable, and no alarming plagiarism issues were found for the experimental group.

Since AI-cheating could be a potential issue, instructors could use AI-detecting tools, such as Turnitin and ZeroGPT, to assist in assessing students' work (Bellini et al., 2024; Walters, 2023). Both tools highlight content that they deem to be AI-generated so that instructors can investigate further. In our study, AI detectors helped us identify six (out of 60) reports of the experimental group for further investigation. One contained minimal revisions from the AI draft. The others were modified significantly from the AI draft but had many statements marked as written by AI, implying intentional use of GenAI to reduce learning effort. While GenAI certainly increased the possibility of academic integrity issues, in our study, we found no evidence of prevalent academic integrity issues. In comparison, more reports were identified as AI written in Spring 2023, indicating GenAI use without permission. Hence, without proactively implementing an AI policy and instructions regarding allowable use of GenAI, some students may rely on GenAI to write a report, causing academic integrity issues.

According to studies done by Rettinger et al. (2004) and Kasler et al. (2023), intrinsic/internal (learning-oriented) and extrinsic/external (grade-oriented) motivations are associated with academic dishonesty. Students with extrinsic/external motivation are more likely to cheat than students with intrinsic/internal motivation. Kasler et al. (2023) also found that students with high external motivation and weak prosocial values are associated with high levels of academically dishonest conduct. This implies that student motivation explains whether they cheat or not, regardless of the availability of learning tools, such as GenAI. The presence of GenAI does not motivate learning-oriented students who recognize cheating is against the social standard to cheat. Guiding students to become learning-oriented may be helpful in dealing with academic integrity issues. A clear policy regarding GenAI misuse with severe penalties alongside teaching ethical GenAI use may further reduce the academic integrity issues. Additionally, Waltzer and Dahl (2023) found that students justify their cheating with concerns such as time constraints and external pressure. Removing such concerns, especially from grade-oriented students, may help reduce academic integrity issues, even in the GenAI era.

We found that 67% of students in the experimental group recognized that submitting GenAI responses as their own undermines academic integrity and 90% to 96.7% of student reports were not flagged by AI detectors. Our data indicates that the redesigned writing assignments that allow responsible GenAI use did not cause major academic integrity issues expressed by educators in previous studies (Farrokhnia et al., 2024; Sullivan et al., 2023; Van Slyke et al., 2023).

Another main concern identified in previous studies is the negative impacts of GenAI on learning, such as overreliance on GenAI and GenAI hallucinations, where students blindly believe inaccurate and false statements produced by GenAI as true facts (Adiguzel et al., 2023; Denny et al., 2024; Labadze et al., 2023; Peres et al., 2023; Yu, 2024). Our survey data showed that students also recognized this concern, and they may have factored in this issue when using GenAI. For the database course, the experimental group, which used GenAI tools, learned unique characteristics of different database technologies at least as well as the control group did. Since 82% of students agreed or strongly agreed that GenAI provides unique insights and perspectives that they may not have thought of themselves, using GenAI to produce the draft might have helped them learn different database technologies.

For the programming course, the experimental group scored significantly higher than the control group on two coding assignments, administered after the redesigned assignment. Even though these assignments were customized, i.e., it is not straightforward to instruct GenAI to produce solutions, it could be difficult to tell whether some students had used GenAI. The two assessed exams were proctored such that students cannot use GenAI to complete them. The exam results showed that the experimental group performed slightly better than the control group. Thus, the availability and use of GenAI tools did not seem to impact student learning of course subjects negatively. Even if some students might have used GenAI to complete the coding assignments, so long as they did not just turn in GenAI's work without thinking, but rather checked GenAI's output to try to understand it, they could still learn course subjects through their interaction with GenAI. Hence, for coding assignments, while detecting misuse of GenAI might be more difficult than general writing assignments, the negative impact of AI hallucination was not an issue.

Our redesign effort shows some potential in teaching how to use GenAI effectively and ethically, although ethical use may need to be taught more. We found that students who used GenAI learned the subjects covered at a similar or higher level compared to those in the control group. The survey did show that students valued GenAI in improving their understanding of course subjects (mean=4.02). We showed that with careful planning and proper implementation, instructors can formally introduce students to GenAI in the classroom and permit ethical use of GenAI in student learning without compromising the quality of learning. However, instructors should educate students about GenAI's capabilities and limitations and the boundaries of ethical use of GenAI. It is critical to teach students basic domain knowledge first before introducing GenAI so that they are capable of trying to avoid mislearning from AI hallucination. The use of GenAI in education should be controlled, and therefore, a proactive approach to integrating GenAI into coursework and curriculum becomes more important.

As AI paraphrasers, such as Quillbot, become more popular, detecting if reports are AI-written may become more difficult. To encourage ethical GenAI use in learning, proper instructions and AI policies should be provided to and discussed with students. Instructors can update assignments with specific, customized tasks so that the requirements cannot be easily met by generic AI outputs and require more interaction with AI to produce valid outputs. Additionally, for report-type assignments, instructors can enforce a threshold on similarity and AI-written score to discourage students from plagiarizing or using GenAI to write reports. For programming subjects, GenAI may be instructed to deliver solutions to coding problems and detecting cheating can be difficult. Yet, as problems go beyond requiring just simple input and output statements, there are usually multiple coding approaches. Oftentimes GenAI may use coding elements that are new to beginners. When used properly, e.g., asking GenAI to explain the new coding elements or identify coding errors, it could be an effective way of learning programming. For assessment purposes, instructors could limit students to only applying elements that have been discussed in class when completing coding assignments. That is, students are encouraged to learn new ways to complete the coding task but are not allowed to use elements that they have not learned yet for assessment purposes. This could, in a way, encourage students to use GenAI for learning while simultaneously discouraging them from using it to cheat.

5.2 Discussion of Findings From AI Survey

One year after ChatGPT was released, we found that students have recognized the importance of GenAI; yet some still have concerns or lack knowledge about how GenAI can be integrated into their learning, since only 37% of students often or always use GenAI during the semester. Students recognized the utility value of GenAI well, but their intention to adopt and actual usage of GenAI did not match up. One reason for this mismatch could be due to their low perceived attainment value of GenAI on improving their writing, analytical, and critical thinking skills, similar to findings by Essien et al. (2024). Students may be afraid of becoming over reliant on GenAI and the negative impact on their soft skills (Adiguzel et al., 2023; Yu, 2024). At the same time, many students recognized that GenAI is useful in helping them brainstorm and improving their understanding of course subjects.

Similar to the findings in previous studies (Labadze et al., 2023; Peres et al., 2023), students realized issues associated with GenAI outputs, such as errors, out-of-context contents, biases, and lack of domain expertise. Since most students as learners may not possess sufficient domain knowledge or sufficient experience with GenAI to evaluate the validity of GenAI outputs, they might not trust GenAI. Additional effort required to validate GenAI outputs may restrict students from appreciating the utility value of GenAI such as saving time.

In terms of learning tools, few students prefer GenAI over traditional search engines to complete writing assignments (16.9%) or learn course subjects (13.8%), and few prefer GenAI over video sites such as YouTube to learn course subjects (28%). This could be explained by students' familiarity and trust with the traditional tools they have been using for a long time. The format difference between ChatGPT's text and YouTube's video might be another reason. Additionally, students can easily check the source of information they received in Google while outputs from GenAI are lacking in transparency, raising trust issues. Interestingly, 41% of students prefer GenAI for completing programming assignments, compared to 22% who prefer traditional search engines. This could be attributed to GenAI's ability to produce customized programming codes while Google can only provide more generic sample codes and explanations of errors. Students should learn when they should use GenAI and when they should take advantage of different tools. This is a skill many businesses are looking for, and therefore, it is important to teach how to properly use GenAI under the supervision of educators.

Since many businesses are looking for opportunities to use GenAI and GenAI skills are the most in-demand skills (Mearian, 2024), college students need to become familiar with GenAI and understand its strengths, weaknesses, and proper use. This is especially important for IS majors, educated to apply IT/IS to create business opportunities and advantages. Prohibiting GenAI in IS courses does not help IS or business students obtain skills and knowledge expected by prospective employers. Educators must find a way to properly incorporate GenAI into their curriculum to train students about GenAI.

6. LIMITATIONS AND FUTURE RESEARCH

While we have controlled some influencing factors in this study, such as instructors and teaching materials, there are still a few limitations. First, the sample used in the study was from one university. We took a quasi-experimental design approach instead of a random sample design. The sample sizes for both the experimental and control groups were limited though still tenable for the statistical tests conducted (Essel et al., 2022; Lee et al., 2022; Moulton et al., 2006; Zhang et al., 2013). Thus, generalization of the results requires further consideration. Future research can use a random sample design with a larger sample in a controlled experimental environment to further validate the findings and provide support for GenAI use in teaching and learning.

We conducted a survey to understand students' perceptions of various aspects of GenAI as a learning tool. Analyzing survey results helps educators understand students' attitudes toward GenAI and provides feedback for effective GenAI teaching approaches. However, we did not measure the intensity or capability of students' GenAI use and its potential impact on students' learning outcomes or their perceptions of GenAI. Future studies can expand this line of research to develop a deep understanding of students' views and usage behaviors of GenAI, especially after they have adequate interactions with GenAI.

We studied two ways of using GenAI to facilitate learning of IS subjects. Future research could investigate different approaches of incorporating GenAI in teaching and their impact on learning. As students become proficient in prompt engineering, it would become harder to detect academic integrity issues in learning assessments. Future research could further examine teaching prompt engineering for learning, using AI paraphrasers, and implementing AI detection tools for assessment since each could have substantial impact on the way we design learning activities and assessment instruments.

7. CONCLUSIONS

To help students become job-ready, it is critical for educators to embrace and be educated about GenAI. In this study, we formally incorporated GenAI into course assignments, teaching students the capabilities and limitations of GenAI, and we assessed two concerns identified in previous studies: academic integrity and mislearning caused by GenAI hallucinations. We found that students are generally aware of the limitations of GenAI and its negative impacts, and we did not observe prevalent issues of academic integrity or AI hallucination. We recommend that instructors apply a holistic view to design learning activities, including some that require GenAI and some that do not allow GenAI. We suggest that educational institutions educate students on becoming learning-oriented rather than grade-oriented, and instructors clearly communicate and enforce AI and grading policies and design customized assignments to deter cheating. Even though the mechanism and reliability of AI detection programs are unclear at this point, it is necessary for instructors to have some sort of measures to detect potential academic integrity issues. Instructors can also demonstrate such tools in class to discourage students from writing a major part of reports using GenAI.

By integrating GenAI into college curriculums, we can not only help students learn course subjects but also help them learn the strengths and weaknesses of GenAI, become capable of choosing an appropriate tool for a specific task, and acquire the on-demand GenAI skills expected by prospective employers. As GenAI becomes more sophisticated, educators need to continually update their GenAI knowledge and practices to provide students with relevant education.

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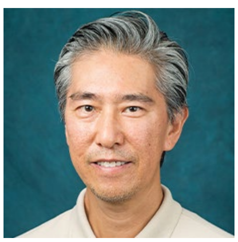

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APPENDIX

AI Survey Questions

Category	No.	Question
Usage	Q1	Before taking this course, I have used generative AI technologies such as ChatGPT.
	Q2	During this semester, I have used generative AI technologies such as ChatGPT.
Knowledge of GenAI	Q3	Generative AI technologies such as ChatGPT can generate output that is factually inaccurate.
	Q4	Generative AI technologies such as ChatGPT can exhibit biases in their output.
	Q5	Generative AI technologies such as ChatGPT can generate output that is out of context.
	Q6	Generative AI technologies such as ChatGPT can generate overly generalized output that lacks in-depth domain expertise.
	Q7	Generative AI technologies such as ChatGPT can generate references that do not exist.
	Q8	Submitting generative AI responses as my own work undermines academic integrity.
	Q9	Generative AI technologies such as ChatGPT might have used copyrighted materials without permission as training data and thus its responses might have violated the original authors' copyright (although it is legal in the US to scrape publicly available contents).
Utility value	Q10	Generative AI technologies such as ChatGPT can help me save time.
	Q11	Generative AI technologies such as ChatGPT can provide me with unique insights and perspectives that I may not have thought of myself.
	Q12	Generative AI technologies such as ChatGPT can provide me with personalized and immediate feedback and suggestions for my coursework.
	Q13	Generative AI technologies such as ChatGPT are a great tool as it is available 24/7.
Attainment value	Q14	Generative AI technologies such as ChatGPT can improve my digital competence.
	Q15	Generative AI technologies such as ChatGPT can improve my understanding of course subjects.
	Q16	Using generative AI technologies such as ChatGPT in the report writing assignment helped me brainstorm on how to construct the report.
	Q17	Using generative AI technologies such as ChatGPT in the report writing assignment helped me improve my writing skill.
	Q18	Using generative AI technologies such as ChatGPT in the report writing assignment helped me improve my analytical skill.
	Q19	Using generative AI technologies such as ChatGPT in the report writing assignment helped me improve my critical thinking skill.
	Q20	Using generative AI technologies such as ChatGPT in the code-correction assignment helped me improve my understanding of coding concepts. (For programming course only)
Adoption intention	Q21	I believe generative AI technologies such as ChatGPT should be integrated into higher education due to its positive impact on teaching and learning.
	Q22	I believe college students must learn how to use generative AI technologies well for their career.
	Q23	I will integrate generative AI technologies such as ChatGPT into my learning practices in the future.
Preference of learning tool	Q24	I prefer to use Google or similar search engines over generative AI such as ChatGPT to complete writing assignments.
	Q25	I prefer to use Google or similar search engines over generative AI such as ChatGPT to learn course subjects.
	Q26	I prefer to use YouTube or similar video sites over generative AI such as ChatGPT to learn course subjects.
	Q27	I prefer to use Google or similar search engines over generative AI such as ChatGPT to complete programming assignments. (For programming course only)

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