

The AURCO Journal is a peer-reviewed, multi-disciplinary scholarly journal published annually by the Association for University Regional Campuses of Ohio (AURCO). The AURCO Journal is dedicated to advancing knowledge through empirical investigation and theoretical analysis. The articles selected for inclusion in the journal reflect the regional campuses' distinct function in Ohio's system of higher education—in particular, their special emphasis on the linkages among teaching, scholarship, and service.

Founded in 1993 at the Lake Campus of Wright State University, AURCO is an association devoted to the professional development of faculty throughout Ohio's twenty-four regional campuses and beyond. The journal welcomes submissions from all academic disciplines and thus includes a diverse mix of writing and documentation styles, which are retained for publication.

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Comments concerning the publication may be forwarded to the Editor.

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The engine of the journal is the reviewer. Without good reviewers, we simply cannot produce a quality scholarly journal. The AURCO Journal currently has stellar reviewers but we need to grow our ranks to increase diversity of backgrounds and disciplines. Diversity will provide a stronger match between author content and reviewer expertise. It ensures a deeper pool of knowledgeable scholars to review manuscripts and allows us to return review decisions to authors faster. More reviewers will enrich the AURCO family. Please consider applying.

Reviewer Qualifications

Reviewers should have published articles in scholarly journals and demonstrate familiarity with the publication process to be considered. A copy of your vita is required.

How to Apply

Changes will be made to the review platform in 2023. Please visit the AURCO website for more information.

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Editor's Commentary

Spring 2025

What Has the AURCO Journal Been Publishing?

I broke a “rule.” When I started as editor of the AURCO Journal 13 years ago I stopped submitting manuscripts because it was a conflict of interest. While I know the current system could *mostly* manage a submission from the editor, the decision to refrain from publishing is still correct.

Then a moment of ethical ineptitude struck. I published a paper in last year’s edition for the 30th anniversary. Thankfully, it was reviewed and accepted. No one called the journal police. The rationalization for the questionable act was centered on the type of article it was. The rational, as it went, was a wonderful way of marking 30 years of publication. Plus, it was super important!

The paper was a sort of meta-analysis of the AURCO Journal’s publication history. It seemed I was in a good position to examine three decades of publications and match them with the journal’s stated mission. The paper titled, “A 30 Year Review of the AURCO Journal” looked at publishing patterns over the lifetime of the journal. Specifically, it examined the guiding criteria for publication. Those suggested guidelines are as follows:

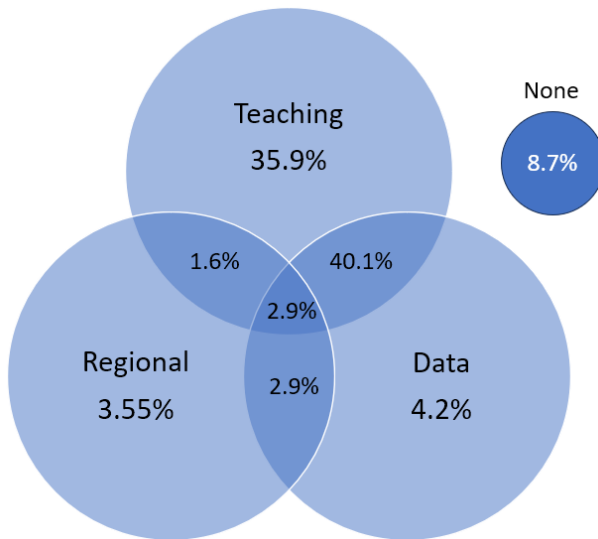
- Teaching or pedagogical emphasis
- A regional campus focus
- Original data

The question was: has the AURCO Journal been published according to these goals? The *general* results showed that published papers were heavily focused on one of the three desired aims of the journal. Papers with a single focus along one of these criteria went like this:

- Teaching or pedagogical emphasis – 44%
- A regional campus focus – 45%
- Original data – 3%

In total, 91% (the percentages above are rounded up) of all articles published in the ARUCO Journal over 25 years (I did not have access to the first 5 years of journals) met at least one of these criteria. That is impressive. It should be emphasized these percentages belong to articles with *only* a single criterion. In other words, a single criterion without the other two being present in the article is what you see above.

If you look at the intersection of articles, in other words, how these criteria overlap, the picture becomes more accurate. The Venn diagram below shows the percentages of articles published in terms of all the criteria. In other words, some papers met a single aim while others had two or three.



There is a lot more to say than, “91% of our articles are on task!” I will tell that to anyone who will listen but other trends stand provide a fuller picture of our publishing history. The fact that only 10.95% of articles focus on regional campus issues surprised me. Please see the article for nuances and more information.

There are other trends to consider but maybe one of you can examine those things. If not, I may need to break the rules again. Maybe I’ll do that for the 60th anniversary.

Thank you,
~Steven Toepfer, *AURCO Journal Editor*



The AURCO Journal...

- is peer reviewed.
- has been in print since 1993.
- is published in April each year.
- accepts manuscripts until October.
- is on EBSCO.
- emphasizes but is not limited to data driven research.
- focuses on but is not limited to teaching.
- focuses on but is not limited to regional campus issues.

The AURCO Journal is now on **Scholastica**. Scholastica is the review platform we use to submit, review, edit, and render decisions about manuscripts. The 2023 volume of the journal was the first to use the platform.



- <https://aurcojournal.scholasticahq.com/>

To submit manuscripts, please visit the Scholastica website or visit the AURCO website at <https://aurco.org/journal>

I hope you enjoy this year's AURCO Journal.

Send questions and comments to stoepfer@kent.edu.

Sincerely,
Steven M. Toepfer
AURCO Journal Editor
<http://aurco.org/journal/>

Awards 2025

Editor's Choice Award for Outstanding Article

**Gen Z - Know them, Reach them, Recruit them,
and the Consequences Should We Fail**

Kelly O'Brien
Bowling Green State University

Michelle Brodke
Bowling Green State University

Outstanding Reviewer Award

Joe Cavanaugh
Wright State University Lake Campus Ohio

Publication Guidelines

Please read the guidelines carefully before submitting a manuscript. **Failure to follow the guidelines will result in delay or rejection of submitted work.**

The *AURCO Journal* publishes only refereed articles.

Style Guidelines & Reference

The AURCO Journal is an interdisciplinary publication which does not enforce a specific set of standardized Guidelines. There is no preferred style for article submissions. However, MLA (Modern Language Association) and APA (American Psychological Association) formats are commonly used but not mandatory. If you cannot use MLA style or APA style, be consistent and professional. Regardless of the demands of your discipline, avoid using abbreviations, acronyms, and jargon. Define or explain all terms. Pay close attention to the format requirements and other guidelines.

Format

Except for italics, and boldface, the document should be free of pagination, word-processing formatting, colored font, and style commands, including headers and footers. **Do not use endnotes or footnotes. Do not embed notes in the document.** Instead use references at the end of the document. **Remove hyperlinks**; remove the link and all HTML. **Use single spaces after periods.**

File Format

Files must be PC versions of Word or .RTF (rich text format). Do not submit PDF or Mac files.

Charts, Illustrations, & Tables

Figures, tables, graphs, and illustrations should be included within the body of the manuscript. This includes .GIF or .JPG files. No other graphic formats are accepted. Make tables simple and attempt to conserve space. **Do not allow tables to extend beyond the margins.** Manuscripts with poorly behaved tables will be returned to the author.

Abstract

An abstract must be included at the front of the paper. Each article should be summarized in an abstract of *not more than 200 words*.

Identifying Information & Anonymity

Place no identifying information in the body of your paper or in the abstract. Identifying information is collected separately during the online submission process. Manuscripts are subject to a blind review process so identifying information may result in the return of a manuscript or a delay. Remove personal names and institutions prior to submitting the manuscript.

Article Focus

The AURCO Journal accepts a wide variety of research including theoretical, pedagogical, qualitative, and quantitative manuscripts. Three factors are preferred but *not* mandatory:

- 1) Manuscripts which include a *regional campus focus*
- 2) Manuscripts with a *pedagogical or teaching focus*
- 3) Manuscripts based on *original data*

Manuscripts are considered strong candidates for publication.

Submission Process

Instructions for online submission can be found on the website (www.aurco.net/journal). Editors will not accept submissions via eMail or on paper. If your manuscript is approved by the reviewers and Associate Editor, it will be submitted to the Editor for final review and approval. Decision letters will be sent to the lead author by the Editor-in-Chief via eMail. Most decision letters are sent in January.



INFORMATION SERVICES

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Refereed Papers

Improving Compliance with Home Exercise Programs in Patients with Osteoarthritis of the Knee: An Evidence-Based Practice Project

Raena Barnes
University of Cincinnati

Osteoarthritis (OA) of the knee is a debilitating condition, leading to a significant decrease in the quality of life and a considerable burden on healthcare systems. A comprehensive literature review was completed, and the evidence identifies OA as the most common degenerative joint disease in the US, risks related to age, gender, and race, and exercise as the most effective nonpharmacological treatment for OA. This evidence-based practice project aims to implement home exercise programs for patients with OA of the knee who are not currently enrolled in physical therapy programs to enhance compliance, patient education, and patient outcomes and promote self-management. This project will be conducted in a medical clinic treating patients with OA of the knee. Those included will be over 50 and have no comorbidities or cognitive or physical limitations preventing them from performing exercises safely. They will be given pre- and post-intervention surveys, with data collected over three months and analyzed via the Chi-Square test to determine clinical significance. This project can improve patient outcomes, including reduced pain, enhanced function, increased self-efficacy, and offer OA patients a cost-effective, sustainable alternative to physical therapy.

Osteoarthritis (OA) of the knee is a prevalent and debilitating condition affecting over 14 million people in the U.S. (Deshpande et al., 2016). One key aspect of managing the knee is the implementation of home exercise programs, which have been shown to alleviate pain, improve function, and enhance the overall quality of life. Chen (2019) noted that exercise is the most successful approach to reducing pain and improving mobility without medication. While home exercise programs can be time efficient and convenient without requiring professional equipment, low compliance rates have been reported, posing a significant challenge in achieving optimal outcomes for individuals with OA of the knee. Studies have reported suboptimal adherence rates to home exercise programs (Chen, 2019), and this lack of adherence limits the potential benefits of

home exercise programs, resulting in increased pain, reduced functional abilities, and diminished quality of life. Barriers to compliance can include pain, lack of motivation, understanding, forgetfulness, and lack of social support. However, the evidence overwhelmingly supports that adopting a home exercise program has demonstrated substantial advantages in improving the well-being of individuals afflicted with knee osteoarthritis. In patients with OA of the knee, engaging in regular exercise can help maintain muscle strength and flexibility and prevent further joint damage and disability. Chen (2019) found that at the end of a 12-week exercise program, most participants noted decreased pain intensity, increased muscle strength, improved balance and mobility, and better quality of life. Educating patients about the benefits of a home exercise program and providing clear, easy-to-understand instructions enhances the willingness to engage in physical activity, thereby increasing the potential for long-term health benefits (Sasaki, et al 2022).

Current evidence indicates that enhancing compliance with home exercise programs is crucial to optimizing knee OA management. Successful interventions have been identified, including education, goal setting, and the use of technology. However, implementing these interventions in real-world clinical settings still needs to be improved, and there needs to be more available knowledge and its application leading to the development of this evidence-based practice project. This evidence-based practice project aims to develop an education program and interventions to increase compliance with home exercise programs in knee OA patients, improve patient outcomes, reduce pain and disability, and enhance overall quality of life. The project will incorporate home exercises, education sessions, clear and concise instruction, and ongoing monitoring and support. It will also utilize technology such as telehealth to enhance engagement and adherence.

Methods

The project intervention includes providing educational sessions to all patients and developing a tailored home exercise program for those unable to attend physical therapy. The population of interest consists of adult patients with unilateral or bilateral knee OA seeking treatment at private medical practice and not currently participating in a physical therapy program. Exclusion criteria include those presently receiving physical therapy or having cognitive or physical limitations, including but not limited

to dementia, Parkinson's disease, balance issues, or chronic pain issues that prevent them from safely participating in a home exercise program.

Patients with knee OA may benefit from viscosupplementation injections, which involve injecting a gel-like substance into the knee joint to improve lubrication and reduce pain. However, in addition to these injections, home exercise programs are crucial in managing symptoms and maintaining joint function. To address the challenges of limited access to physical therapy, the project intervention involves the Nurse Practitioner (NP) providing education sessions to all patients and a home exercise program specific to improving knee mobility (see Appendix C). These sessions aim to educate patients about OA, how it affects their knees, and the importance of regular exercise, proper technique, and specific exercises tailored to their needs and physical abilities, including stretches and range-of-motion exercises. Those able are also encouraged to include walking or swimming in their regimen. The NP will conduct weekly follow-up phone calls to ensure compliance with the home exercise program. Together, these interventions allow for a comprehensive and holistic approach to patient care, addressing knee OA management's medical and rehabilitation aspects. Patient enrollment was voluntary, with patients giving verbal permission before their education session. Data collection includes pre-intervention surveys obtained during the education sessions and post-intervention surveys collected at the end of three months. These questionnaires use a Likert scale developed in-house (see Appendices A and B) to assess if they understood the educational materials, how frequently they exercised pre- and post-intervention, their perceived benefits, any barriers encountered, satisfaction with the home exercise program and education session, and compliance with prescribed exercises post-intervention. The data collected will then be analyzed using the Chi-Square test. Compliance is a categorical variable, and the chi-square test will determine if there is a significant association between education and follow-up versus education alone in increasing compliance rates with the home exercise program among participants (see Appendix D).

Results

Over three months, the 20 participants who met the criteria for inclusion in this evidence-based practice project self-reported their home exercise participation and their OA symptoms, and it was found that the

percentage of those who were compliant with a home exercise program increased from 40% to 70%.

In Phase I of the project, a team led by an NP analyzed barriers to patient compliance with home exercise programs for patients with knee osteoarthritis (OA). Critical interventions that were tested and implemented included developing an educational curriculum to impart a thorough understanding of OA, its progression, and its impact on mobility, as well as a tailored home exercise program consisting of six stretching exercises that could improve OA symptoms and increase knee mobility.

In Phase II, strategies were developed to improve participant compliance. These included providing pre- and post-intervention questionnaires to patients to assess their understanding of education programs and exercises and follow up with the provider to evaluate individual performance and compliance reports.

In Phase III, the project began by implementing critical elements. A new patient education and home exercise program was developed based on the steps, weaknesses, and challenges identified in the process. The Nurse Practitioner collected data through patient interviews and reported it during the sustainability phase to monitor compliance and identify decreases, obstacles, and challenges.

Among the 20 participants in the project, before attending the education session, 40% understood that exercise was beneficial for managing symptoms associated with osteoarthritis, and 40% participated in some form of regular exercise. After attending the education session, 100% stated they understood the benefit of exercises for symptom management, and the percentage of participation in exercise increased to 70% at the end of three months. This is seen in Chart 1 (Table 1).

Table 1: Education and Exercise Awareness Pre- and Post- Intervention

	pre-intervention yes	Pre-intervention no	Post intervention yes	Post-intervention no
Benefit aware	8	12	20	0
Active exercise	8	12	14	6

Note: N=20

When the two groups were compared, the participants who attended the education session and regularly interacted with the NP were noted to participate at some level with their home exercise program more often than those who only participated in the education sessions. This indicates that provider intervention is beneficial but unnecessary for successful implementation (Table 2).

Table 2: Exercise Program Compliance Based on Intervention

	Education and follow up	Education only
Performed all exercises	2	1
Performed >50%	3	2
Performed <50%	4	2
No exercise	1	5

Note: N=20

All 20 participants were contacted at the end of the three months, with one reporting a hospital stay that affected their compliance. As a result of contacting all participants, no patient information was excluded from the project. While not a marker, during post-intervention patient interviews, 60% of participants noted decreased pain and increased knee mobility with prescribed exercises.

Limitations

One limitation of this project is the small sample size of 20 participants, which reduces the statistical power and generalizability of the findings. With a small group, the results may not accurately reflect broader trends or be representative of a larger population. Additionally, individual differences, such as motivational levels, baseline knowledge, or personal barriers, may have a greater impact on compliance rates in a small sample. Other limitations include potential self-reporting bias, as participants may overestimate their adherence to home exercise programs, and the lack of control over external factors (e.g., support systems, physical ability) that could influence compliance. Future studies with larger, more diverse samples and objective adherence measures could strengthen the validity of the findings.

Discussion

Over three months, this project yielded two key findings. The first is the increased understanding of the benefit of exercise in managing knee

osteoarthritis (OA) among the participants in the project after attending education sessions. Pre-intervention surveys revealed that only 40% of the participants fully comprehended the importance of exercise, while post-intervention surveys showed a substantial increase to 100%. The second is that the intervention led to an improvement in compliance rates among patients. The compliance rate increased from 40% to 70% among all participants, demonstrating the effectiveness of the educational sessions.

Most participants in the project noted improved mobility when discussing the benefits of exercise in follow-up visits with the NP at the end of three months. The benefit of improved mobility can lead to improved quality of life and increased adherence to the home exercise program due to this positive outcome. The project transformed individuals, increasing resource utilization and reducing reliance on pharmacological interventions. While the project's outcomes were largely positive, some discrepancies between the observed and anticipated results were noted. These discrepancies can be attributed to individual variation. Although all patients reacted favorably to the educational sessions, compliance differed based on co-morbidities, OA severity, and personal motivation. Two participants (n=20) from the group of twenty were briefly hospitalized, which affected their ability to complete the prescribed exercises during the three months. Other factors, including social support, may have influenced patient compliance. It is important to note that factors such as patient self-reporting of compliance and the potential for information bias may introduce limitations to internal validity. Additionally, the project has relatively small group sizes, which may impact the generalizability of the findings. To reduce the influence of small group sizes and enhance the generalizability of the findings, future studies may involve a more extensive and diverse patient population, allowing for further exploration of factors influencing compliance and refinement of interventions.

The findings of this project have practical implications for clinical practice. Healthcare providers can use education sessions and follow-up to enhance compliance with home exercise programs and improve OA management and patient outcomes. These interventions can also be modified for more diverse or rural patient populations with limited access to healthcare providers, and technology can be utilized to monitor patient outcomes and symptom management.

The sustainability of the project's interventions largely depends on healthcare providers' commitment and integration of educational

components into routine care. Additionally, the project's success makes it a strong candidate for implementation in other clinical settings, promoting the potential for benefit spread to a broader range of patients with knee osteoarthritis. This evidence-based practice project underscores the importance of patient education and provider follow-up in improving compliance with home exercise programs for patients with knee osteoarthritis. Healthcare providers should consider integrating these interventions to improve patient outcomes.

To build on the success of this project, future research should investigate the long-term sustainability of improved compliance and its impact on disease progression as well as healthcare costs for osteoarthritis patients. Also included should be the exploration of digital tools and telemedicine for education and follow-up interventions to increase patient access and convenience. The cost-effectiveness of the interventions to inform healthcare resource allocation should also be examined.

In conclusion, this evidence-based practice project demonstrates a path toward transformative change in managing knee osteoarthritis (OA). Through comprehensive education and provider intervention, there is a noted shift in the paradigm of patient compliance and overall health and well-being. Emphasizing the significance of these interventions, the investigators enhanced the quality of life for those affected by OA and implemented a program that can reduce healthcare costs. This project emphasizes the importance of patient education and provider engagement in managing chronic conditions. Moving forward, the care of patients with OA can be redefined, and similar programs can be encouraged across medical disciplines, creating a healthier, more informed, and empowered population that reaps the benefits of improved quality of life.

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Appendices

Appendix A**Data Collection Tool Pre-Survey**

- 1) Where is your osteoarthritis located?
 Right knee Left knee Bilateral (both)
- 2) Do you currently exercise?
 Yes No
- 3) Do you understand that exercise could help manage your osteoarthritis symptoms?
 Yes No

Appendix B**Data Collection Tool Post-Survey**

- 1) I attended a home exercise education session
 Yes No
- 2) I understood the exercises and how to perform them correctly
 Yes No
- 3) I did the exercises exactly as described in my home exercise plan
 Yes No
- 4) I did more than half of the exercises in my home plan
 Yes No
- 5) I did less than half of the exercises in my home plan
 Yes No
- 6) I did not exercise
 Yes No

Please explain factors that limited your ability to exercise (e.g., time, illness)

Appendix C

Education Session

- 1) Provide an explanation of OA of the knee, including causes and symptoms. Show the participant their x-ray and explain how OA has impacted their knee joint.
- 2) Explain the benefit of exercise and the importance of compliance and consistency to improve symptoms of OA and pain management
- 3) Explain and demonstrate safe and effective exercises for OA, including stretches (quadricep stretch, straight leg raises, hip abduction, hip flexion, hamstring curl and stretch), gentle ROM of affected knee(s), aerobic exercise, weight bearing (walking) as tolerated, and non-weight bearing (swimming or water aerobics, chair aerobics). Proper form and technique will be demonstrated with repeated action performed by the patient and printed materials provided.
- 4) Safety discussed to include avoiding overexertion and seeking medical evaluation (e.g., increased pain).
- 5) Realistic and attainable goals set based on patient ability to include times per week and repetition.
- 6) A follow-up schedule will be set to monitor progress and adjust the program as needed.

Appendix D

Chi-square results

	Phone call/Education	Education only	Row totals
All	2 (1.50) (0.17)	1 (1.50) (0.17)	3
➤ Half	3 (2.50) (0.10)	2 (2.50) (0.10)	5
< Half	4 (3.0) (0.33)	2 (3.0) (0.33)	6
None	1 (3.00) (1.33)	5 (3.0)(1.33)	6

From the data set, I compared the frequency using a Chi-Square Test with 95% confidence. From this test, the resulting p-value was 0.21.

Leveraging AI to Enhance Critical Thinking Skills

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The perils and possibilities of artificial intelligence present educators in the 21st century with challenges incorporating new forms of technology into the learning environment. Technology's ever-evolving nature has not only given educators more means to teach in general but has also enhanced the demand for critical thinking abilities (Halpern, 1999). Personalized learning, access, innovation, and efficiency present unprecedented opportunities to incorporate emerging technologies into the classroom environment both online and in person. Concerns regarding bias, privacy interests, lack of transparency and inaccurate information give many educators pause in embracing new technologies. Because it is now so simple to obtain enormous volumes of information, the ability to evaluate and assess its quality is paramount (Walton, 2017). Much of the information available online is unreliable (Flanagan, 2010). As a result, one of the most important critical thinking skills that should be openly and frequently taught starting in college is the ability to assess the dependability of an information source (Goldman & Brand-Gruwel, 2018). Artificial intelligence has the potential to revolutionize teaching and learning, but it must be implemented thoughtfully, with careful consideration of ethics, privacy, and accuracy to maximize its benefits and minimize its risks. This paper discusses three case studies, from three different disciplines at a regional college of a research university, illustrating the use of artificial intelligence in the classroom to enhance critical thinking skills.

Critical Thinking and Academic Success

Critical thinking is the kind of thinking about any topic in which a person improves the quality of his or her thought processes by elevating the

caliber of their reasoning by deftly controlling the thought processes that are inherent in thinking and applying intellectual standards to them (Paul & Elder, 2004). It is the intellectual process of "conceptualizing, applying, analyzing, synthesizing, and/or evaluating information gathered from, or generated by, observation, experience, reflection, reasoning, or communication" (Scriven & Paul, 1987, para. 2). Higher-order thinking from Bloom's taxonomy is synonymous with critical thinking in the realm of education (Anderson et al., 2001). Cognitive abilities can be categorized based on their complexity level using Bloom's taxonomy (Anderson, et al., 2001). Therefore, the levels of analysis, synthesis, and assessment correspond to higher-order thinking abilities (Anderson, et al., 2001). The goal of critical thinking is to find a way to consider information in a more complex fashion, to enhance problem solving skills, to communicate more effectively, increasing collaboration and innovation (Roth, 2013). The benefits of critical thinking inure to the enrichment of personal development as well as organizations and the community (Roth, 2013).

Researchers and practitioners have encouraged a focus on critical thinking to equip students with the skills needed for academic success and twenty-first citizenship (Crane et al., 2003). Research has shown that when critical thinking skills are developed in the classroom, not only are students more thoughtful in the learning environment, but they continue to practice those skills in their lives (Murawski, 2014). Moreover, studies have suggested that acquiring critical thinking skills is a better predictor of making sound judgments than IQ (Butler et al., 2017). While a historical focus on critical thinking has permeated academic circles, developing students' critical thinking skills is also now necessary to assist in evaluating the legitimacy of information from among the volume of material available on the internet (Yang et al., 2008). It is not enough to acquire knowledge. The ability to analyze, weigh, evaluate, contextualize, and assess that knowledge is what makes it valuable (Debono, 2004).

Given the importance of critical thinking skills for individuals, academic success and society, the fact that such thinking is a skill set that can be developed is good news for all. Educators are then faced with the task of how to effectively develop critical thinking skills for learners in the 21st century. Research reveals the emergence of two approaches to developing critical thinking skills in the classroom. Some educators prefer a definitive and overt teaching of critical thinking as a separate subject (Abrami et al., 2008). The predominant approach is to endeavor to nurture

their students' critical thinking abilities by incorporating them within the framework of their respective subjects (Caceres et al., 2020). This is achieved by emphasizing the fundamental principles of each academic domain, selecting topics that facilitate students' comprehension of the world through the lens of the subject matter, and acquainting them with discipline-specific methodologies (Caceres et al., 2020). Through this approach, students are encouraged to cultivate solutions by applying the essential skills inherent to each field of study (Jones, 2015). The authors of the current case studies have chosen the latter approach to integrate artificial intelligence technology and the development of critical thinking skills.

AI in Higher Education

While artificial intelligence has been in the lexicon and components of AI have been at the fingertips of many for several years, the last few years have witnessed unprecedented growth in this field. Artificial intelligence refers to machines that can examine data, make inferences and act accordingly (Roschelle et al., 2020). Numerous definitions also characterize machines as learning entities due to their capacity to adjust to fresh challenges and draw conclusions from engagements with other data-providing entities, in addition to interactions with humans (Niemi, 2021). Current artificial intelligence technology is designed to build a computer network that resembles the “neural networks of the human brain (Niemi, 2021, para. 7).” With this capability has come widespread optimism about the potential for artificial intelligence to enhance classroom learning. For example, researchers have discussed the promise of AI bringing the possibility of more personalized learning for students (Hwang et al., 2020), as an analytical tool for understanding student functioning and needs (Seo et al., 2021), as a resource for automating routine tasks (Popenici & Kerr, 2017) and as a method for increasing access to educational resources (Roll et al., 2018). The pervasive nature of the technology has led commentators to conclude that “there is little doubt that the [AI] technology is inexorably linked to the future of higher education” (Olaf et al., 2019, p. 39).

However, many have also urged caution in the rush to embrace the new technology. Concerns have been raised about the ethical impact of artificial intelligence. Many observers have discussed the problem of AI generated writing assignments including the academic integrity issues

presented as well as the impediment to student development in both writing and critical thinking skills (Marche, 2022). Educators have communicated worries that too much dependence on AI systems might hamper students' capacity for self-learning, creative problem solving, and critical thinking (Wogu et al., 2018). Others have noted that AI generated content is frequently incorrect and misleading (Perkins, 2023). Perkins recently published an observational study of ChatGPT, a popular and publicly available, large language model AI tool, which is capable of producing large amounts of text in response to short input requests (Perkins, 2023). Perkins prompted ChatGPT to respond to a question explaining ChatGPT's own capability. The prompt requested the response to be written in an academic style with citations in APA format. ChatGPT responded with valid information about its own capabilities, but all the references provided were fictitious (Perkins, 2023). Others have noted the risks of gender, ethnic and political bias embedded in AI models and the output generated (Rozado, 2023).

Although AI poses risks to academic integrity, it also opens doors to various opportunities. AI has the capacity to enhance users' capabilities, both positively and negatively (Foltynek et al., 2023). Thus, it is important to educate students about the advantages and constraints of AI tools (Seo et al., 2021). This knowledge equips them to use AI ethically and effectively (Foltynek, et al., 2023). As contemporary societies become more automated, individuals will likely also employ AI tools professionally (Foltynek et al., 2023). Consequently, integrating AI education into their learning experience becomes imperative, offering them the chance to acquire and utilize these essential skills ethically and effectively.

Current Case Studies

The current case studies involve observational and qualitative data collective from three separate courses, each delivered in a different course modality, in three separate disciplines at a regional campus of a research institution. The college attracts a high percentage of minority and first-generation students. The particular courses involved in this case study consisted of first- second- and third-year college students from a variety of different majors. The purpose of this paper is to explain the strategies used by the authors to attempt to integrate AI learning into the classroom setting, discuss the pedagogical impact and implications for the future. Each author aimed to integrate critical thinking with the utilization of AI in the form of ChatGPT, tailoring the application to their respective academic field.

Case Study 1

The first assignment involved a face-to-face course in an information systems class and unfolded over a series of three class sessions. The introduction to ChatGPT was centered around the midterm examination. First, students were given a midterm exam involving short answer questions. In the second class meeting, the course instructor provided an overview of ChatGPT, its origins, objectives, and functional mechanisms. The instructor initiated a discussion with the class conversing about their prior knowledge and experience with ChatGPT and their expectations for how it can be used in various academic, social and workplace settings. The instructor then conducted a demonstration by posing a question to ChatGPT and allowing students to see the response. Students were then divided into groups and asked to set up a free version account with ChatGPT and then invited to interact with the technology posing questions and prompts and reviewing the answers generated. From the small group experiential exercise students were asked to come back into the larger class discussion to discuss their experiences. The instructor discussed the capabilities and limitations of the technology. The instructor then guided the class in a discussion of the ethical parameters of using AI responsibility. Students discussed positive aspects of the technology, the possible downsides of machine learning and the future development of AI.

In the next class setting, students were asked to reform their small groups and retake the midterm examination with AI assistance. The instructor then handed back the original graded midterms and asked students to compare their answers to the AI generated answers. Students were asked to reflect on the similarities and disparities between the exams completed by students and the exams completed by AI. The discussion groups were asked to review how closely the AI responses aligned with the correct exam answers. The small groups were then asked to discuss the insights the group gained in this comparison with the larger class. The larger class discussed the ways in which the AI generated answers varied widely in their accuracy.

There were several learning objectives for this activity. First, it was designed to assist students in describing and evaluating the circumstances where AI may furnish inaccurate information. This involves critically assessing the reliability and precision of AI-generated content. Additionally, the activity encouraged students to contemplate the notion that AI's output

often hinges on the quality of input data and the context it operates within. It prompts students to consider how AI-generated materials, although occasionally accurate, may not always align perfectly with the specific learning material covered in a particular course. Furthermore, the activity sought to foster an investigation into the limitations of AI. It underscored the importance of recognizing these limitations and highlighted the necessity of acquiring foundational knowledge before relying on AI as a learning tool.

Before launching this assignment, the instructor opened a dialogue with students about their experience with and impressions of AI technology like ChatGPT. Most students had heard of ChatGPT but had not interacted with it. Students expressed fears that platforms like ChatGPT could be abused in the classroom. Most recognized that relying on AI technology like this to complete assignments felt like a violation of the directive that students submit their own work. Students also expressed a desire to use the technology to help complete complex tasks or work they did not fully understand but did not want to become dependent on it or have it negatively impact their learning. Qualitative feedback was solicited from students regarding the assignment and was overwhelmingly positive. Some students expressed excitement over the chance to interact with ChatGPT – something they had heard about but not yet experienced. Other students admitted to having used the technology in other courses without understanding the implications of doing so. Several students talked about the ways that their analytical ability had been expanded by having the tools to know when and how to employ the technology.

Table 1. Qualitative responses collected from student survey question in case one: What are the ethical aspects of using AI in the classroom? (N=6 of 25 student responses)

- *I've heard some mixed things. I've heard it's this super smart AI that can help with homework and stuff, which sounds cool. But I've also heard that it might make us lazy, like relying too much on it could be a bad thing.*
- *I mean, it's incredibly smart, and that's what's scary. It can answer almost any question which can make it tempting to use all the time.*

But, I've seen some friends become overly dependent on it, and it feels like it might be making us lose our ability to think on our own.

- *I gotta say, I love ChatGPT! It's like having a magic homework genie. I can ask it anything, and it helps me breeze through assignments. I've got more free time to hang out with friends and enjoy my freshman year of college. People say it will make us lazy, but I'm not complaining, your first year is like a refresher of high school. Like none of these classes are about the things I came to college to learn about.*
 - *Not gonna lie, I imagine it being like the terminator. It's eventually going to be the end of civilization.*
 - *I don't feel like I know enough about it to have an opinion. I mean I've heard about it, but like it doesn't sound legal.*
 - *This sounds like that social media documentary we watched in class. There is some sort of catch because nothing is free!*
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Case Study 2

The second case was an assignment in a fully online business law course, which involved an experiential exercise requiring the creation of a legal contract. Prior to the introduction of this assignment students worked on a role-playing exercise where they assumed the role of an attorney representing a limited liability company (“LLC”) with the objective to protect that LLC’s intellectual property. The instructor provided background information on the creation of common legal documents and the historical use of templates in the creation of contracts. Students were first asked to draft a legal contract incorporating the terms required by their fictional clients from either a template provided by the instructor or utilizing an AI tool (ChatGPT or similar) to produce a legal document that satisfied an assigned fact pattern. Students were then required to reflect on their experiences and discuss the ways that using AI helped in the creation of the document and the ways that AI was limited in producing a viable contract. The instructor asked students to reflect on the unique ethical issues of providing AI technology with protected client information and related privacy concerns.

After the assignment the instructor elicited qualitative responses from students about the project. Students expressed concerns about using AI in this context. The survey question was “Based on your experience with your Final Project, would you use AI for future assignments (where allowed) to help you think critically? Please explain why or why not.” Of the 11 students (out of 25) who completed the survey questions, six responded they would use AI on future assignments and five responded they would not use AI on future assignments. Students were apprehensive about divulging information to ChatGPT and losing control over how that information might be used in the future. The use of templates with basic contract language and provisions from which students could pick and choose and modify to fit their fictional client’s needs seemed to be of greater benefit to students than giving ChatGPT the information they possessed to create the entire contract. Student feedback did reflect finding value in the ability to use ChatGPT to gain understanding of legal vocabulary and concepts and for help with ideas to get started on a project. Students also commented on the ability of AI to do the work for the student in an academic setting and the negative impact of missing out on learning opportunities as a result.

Table 2. Qualitative responses collected from case two student survey question: Based on your experience with your Final Project, would you use AI for future assignments (where allowed) to help you think critically? Please explain why or why not (n=11 of 25 students responded to survey).

- *Yes, I would use AI if allowed. The reasoning for this is allows me to better understand while also conducting the research on my end which would allow me to learn more about the information that I am learning. With the Cognitive Computing I do think AI will have better wording and terms than I would personally use while also teaching me.*
- *I think AI could be helpful, but I think it is a very fine line between it helping with assignments and actually doing the work for you ... I think that in some ways it would be helpful to make things easier to understand, but I think it can take away a student’s ability to have to learn the material and put in the effort.*
- *I would one hundred percent use AI to help me come up with some sort of template to follow. We always talk about ChatGPT for machine learning at work, I just did not think to use that resource for*

a school assignment ...

The reason I would use AI for this assignment would be it can resemble a conversation I am having with a human. I have even seen videos where Chat GPT has prompted to “dumb down” an article for the end user. This could’ve been useful to copy and paste then ask AI to simplify the reading.

- *I do not have much experience with AI, but from the information coming out in the news about AI, I would have to say probably not. I enjoyed using the templates because I was able to take out and add what I needed that related specifically to my documents. I also feel that the templates give a greater understanding of the legal terms for the documents. Using the templates that I found, I was able to take out many sections that did not apply to my documents and add in sections that I believed would give my documents more legal power.*
 - *Overall, I would not use AI for future assignments. Do I think it could make it easier on the student? yes. However, I believe that if most of the work is done for the student, then they don't have the traditional learning experience. They could find it hard to understand the assignment or be able to come up with certain things on their own without it.*
 - *No. I've never used AI before, but I think I would wait a few more years for it to improve.*
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Case Study 3

The third case study involved a fully online criminal justice course and asked students review a news article (Weiser and Schweber, 2023) about a lawyer who asked ChatGPT to write a legal brief. The lawyer submitted the brief to the court. However, the opposing party raised objections when the legal citations used in the brief could not be located. It was later learned that ChatGPT fabricated the legal citations. The attorney had not checked any of the ChatGPT citations before filing the brief. Students were asked to read the article and draft an essay reflecting on what happened in this case, why the attorney used ChatGPT to write the brief and the lessons they learned from this story. Students discussed the

danger of relying on internet to conduct legal research, expressed their surprise that an attorney would fail to check the legal citations and expressed surprise that ChatGPT would generate false responses. Information literacy with regard to misinformation on the internet came up repeatedly in student responses as did the acknowledgment that it is important to seek out reliable sources when completing academic assignments as well as real world projects.

Table 3. Qualitative responses collected as part of the extra credit assignment in case study three: What is your experience with ChatGPT? What concerns do you have about this technology? (N=5 of 23)

- *I do not have much of an experience with ChatGPT, since I am very against its usage in the classroom setting, and a very large amount of students are now currently able to complete all of their work with it, and get good grades by putting in no effort. I have logged onto ChatGPT one time to see what it was about, but after I used it for a couple of minutes I started to better understand exactly how powerful this technology could be.*
- *I personally have only used Chatgpt for the sake of an assignment our teacher told us to use it for. I know for we had to use Chatgpt to prove a point our professor was trying to make. We had to type in our topic for a project and see what It could come up with. I personally did not like It because I felt like It was not giving me what I was asking/looking for, which made it even more difficult and frustrating for me to use.*
- *My experience with ChatGPT is that I have heard of it but I have not ever used it. All I know is that it is a artificial intelligence that kids use to complete assignment. Which I believe is wrong because how are you supposed to learn what you are going into if you take a short cut in life.*
- *My experience with ChatGPT is that to my knowledge I don't think I have ever heard of it before. What concerns I do have about this technology is the human rights and business aspect of ChatGPT. Its*

AI a machine it does not feel anything. It could spread stuff like hate speech.

- *My experience with ChatGPT was interesting because it is a great source to learn and understand information, however further research is needed in order to back up information. My concerns with this technology is misleading people with information that could leave them astray and then them thinking they know what they need to know when they may not.*
 - *My experience with ChatGPT is minimal, but I have utilized it for social aspects. For one of my courses, we had to write a paper about AI, and the professor encouraged us to use any type of AI generator that could assist in constructing our project. I used ChatGPT for the first time and was shocked at how it constructed an entire essay within seconds.*
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Considerations for the Future

The growing prevalence of AI in our society requires engagement from the academic community. This paper illustrates three examples of how AI can be used to foster critical thinking skills in the classroom. When evaluating the insights derived from the examined case studies, it is important to highlight several noteworthy observations. Many students exhibit curiosity regarding AI, with a significant portion already incorporating it into their activities. Lack of exposure to ethical AI education for students can increase the likelihood of them resorting to improper AI utilization, potentially leading to academic misconduct. These case study observations thus confirm prior commentary by others (Foltynek, 2023). Leveraging AI for pedagogical purposes has the potential to enhance students' critical thinking abilities. Classroom activities such as those described here are beneficial in assisting students with information literacy skills, recognition of the limits of artificial intelligence, increasing student confidence in their own abilities to comprehend and apply their knowledge, and in thinking with more nuance and complexity about the ethical use of information.

The case studies presented here warrant further investigation, including the collection of quantitative data to explore the impact of incorporating AI assignments on overall student performance. Additional

qualitative data should also be collected in broader surveys evaluating students' impressions of interacting with this technology. Survey data that includes both students who complete AI course activities and those who do not may be helpful to elicit a more robust response from feedback for comparative purposes. One goal is to better understand the current openness to AI as an educational tool and to explore options for developing more effective assignments. Additionally, future research should explore how students' viewpoints change over time. These initial studies illustrate the caution with which many students approach the new technology. As students become more comfortable with the use of this AI, reticence on using these tools will most likely dissipate over time if, as predicted by the experts discussed above, AI becomes incorporated into greater aspects of daily life.

Future research should also focus on the experience of faculty in interacting with AI technology and its use in the classroom. While not specifically the focus of this study, the faculty engaged in these case studies were accustomed to using technology and exploring new technological advances in the courtroom. It is imperative that faculty who choose to explore activities such as those described in this paper first become familiar themselves with the concept of artificial intelligence, what it is capable of, how it works and the implications of its use. The novel experience of using this technology may be outside the comfort zone and experience of many. Given the broad reach and complicated repercussions of artificial intelligence discussed above, faculty must take time to gain competence in uses and limitations of the technology before bringing it into the classroom. These case studies and student adaptability to this technology suggests that faculty cannot afford to ignore the emergence of this technology and its impact of students whether faculty ultimately decide to employ activities involving AI or not. It is imperative that faculty consider this technology and provide clear parameters for the use of AI to help guide the student to address ethical concerns and to meet educational competencies.

There is still much work to be done to consider the risks and benefits of this technology in the academic setting and beyond. For example, colleges and universities should consider adopting policies around the use of AI, outlining the parameters within which use is considered acceptable and where it would violate principles of academic integrity. Researchers should investigate the ways in which students and faculty currently use AI and the level of understanding around the technology.

Professional development explaining the technology, how it works, its capabilities and ideas for pedagogical integration should be implemented. In order for educators to actively engage in discussions about the proficient utilization of AI, they must possess a comprehensive understanding of the technology. Artificial intelligence in education holds the promise of ushering in significant advancements in the learning process (Niemi, 2021). However, realizing this potential requires substantial investments in research that bridges the realms of human learning and intelligent machine learning. There is a pressing need for an increased focus on fundamental and practical research in the field of AI, particularly with regards to utilizing multimodal data (Niemi, 2021).

While the scope of artificial intelligence and its rapid expansion can be intimidating, pedagogical interventions such as those described here illustrate the possibilities the technology holds to support, rather than detract from student learning. If, as Francis Bacon famously said, “knowledge is power” (Vickers, 1992, p. 512), then educators have a responsibility to assist students in harnessing that power and wielding it ethically and effectively. The assignments outlined here provide examples of mechanisms by which this can be done with AI in a way that enhances critical thinking skills while integrating this new technology into the toolkit of student learning.

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Enhancing Teaching Efficiency – A Design Model

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Efficient teaching reduces instruction preparation time and effort while improving student learning effectiveness. This paper provides instructors with teaching methods that can improve learning outcomes and reduce student studying time while reducing time spent in instruction. This paper uses both individual experiences and evidence from the literature to demonstrate how course design and method of instruction can yield significant student performance gains while reducing faculty preparation time. The importance of empowering students to improve student learning and teaching efficiency, the opportunity to enhance efficiency arising from teaching courses in multiple modes of instruction (in-person, online, hybrid), and the effective use of AI for efficient instruction and learning will also be addressed in this paper.

Introduction

Efficiency, as defined by Oxford Reference A Dictionary of Business and Management (Law, 2009) is, “A measure of the ability of an organization to produce the maximum output of acceptable quality with the minimum of time, effort, and other inputs.” This paper seeks to suggest teaching methodologies that can achieve learning outcomes by using efficient teaching methods. Efficiencies that focus on enhancing revenue, such as assigning more students per instructor, reducing the quality or quantity of material covered, or lowering the assessment standards of the course are not considered. Teaching efficiency here is defined by maximizing student performance while minimizing the ongoing efforts on the faculty’s part. As workloads of faculty steadily increase, the need for an efficient use of time and resources is becoming ever more important.

Increased Workload

Efficiency is becoming more important as instructors are steadily being asked to do more with less time and resources. According to the American Council on Education (2022), faculty workloads have grown since the pandemic. These increased workload demands come as institutions face lower enrollments and reduced state support leading to institutional budget constraints (Fischer 2022). This includes not only course load schedule but also additional administrative tasks such as student advising (both formal and informal) and recruitment and retention work for student enrollment. Tenured faculty continue to be under pressure to research and publish with less resources both with student assistants and finances. These budget issues limit the resources available to support teaching, conduct research and hire additional instructors. The increase in workload is not limited to instructors. Almost two thirds of higher education management and teaching and learning professionals also report having excessive workloads that are leading to “burnout” (Muscanell, 2024). This negatively impacts the amount of teaching and learning services available and their effectiveness, which can in turn increase the workload of instructors who are forced to take on these tasks. Teaching efficiency is important as faculty navigate their work and life balance.

Instructional Efficiency

One way to mitigate the higher faculty workload expectations and potential burnout is through improved efficiency in teaching. The design of the course, method of instruction, assessment and feedback and appropriate use of ancillary materials can all provide significant efficiency gains. There are certainly overlaps in each of these four areas as they relate to student learning and instructional efficiency. In general, by investing in modest changes to how courses are designed and taught, instructors can enhance learning while reducing their ongoing course instruction and set-up efforts.

Course design

A stitch in time saves nine....

In designing the course, the syllabus has been found to be key to efficient instruction. This may take more preload effort but is worth it. The National Council for Accreditation of Teacher Education (NCATE 2010) states that Instructors should have well organized course structure and objectives,

clearly defined assignments, and effectively connect the learning activities to appropriate assessments. Research shows that students will not only view these instructors as more knowledgeable but can learn in these more organized courses (Educational Testing Services 2014, Bain 2004, Teitel 2004). Providing students with specific activities, assignments, and deadlines gives a clear understanding of what is required for being successful in the course. Students will also benefit from guidance on how to obtain help. Frontloading valuable information at the beginning of the semester and providing the information in the syllabus reduces student confusion and improves efficiency.

Although Instructor availability to students is necessary, clearly outlining other available resources can often provide students with options that can more quickly and effectively address their needs. For example, peer tutors have been found to significantly improve student academic performance (Leung 2019; McMaster, Fuchs, & Fuchs, 2006). Tutors are available at our campus, and students who have gone for help have found them worthwhile. For example, information on how to arrange for tutors, how to participate in student lead study tables or how online resources like YouTube and generative AI can be used to review or test their understanding. Students can also be pointed to the appropriate campus help desks for issues that involve technology, learning platforms or library resources.

In addition to instructor availability, utilizing a classmate friend is highly encouraged. Many students come to university with the habit of their K-12 teachers providing them with missed material, notes or handouts. For in-person class, encouraging students to pair with another classmate not only helps them to form friendships, but also provides them with someone to ask questions with that may be less intimidating than the instructor. This reduces the number of times you are asked the question of “What did I miss in class?” Classmate friends are most efficient for in person courses where excused absences may be made up, if possible, or notes were given.

Frontloading information on the use of Artificial Intelligence (AI) is necessary for the class to run efficiently. Instructors should consider including statements on the permissibility of the use of generative AI, and student conduct in their syllabus. These are particularly important when teaching in a hybrid or fully online format where a substantial portion of the course work is online and often asynchronous. Providing a summary of the institutional student code of conduct and a link to the full policy will go a

long way towards highlighting its importance and saving instructors from headaches later. For example, including something like, “It is the policy of X University to uphold standards of honesty and integrity, and enforcement of these standards are viewed as critically important. Any misconduct including cheating on exams, collaborating with fellow students, when not permitted, or using other’s words or ideas without providing credit to the source are subject to disciplinary action.” Similarly, a statement on the acceptable use of generative AI is important. For example, “The use of generative AI such as ChatGPT, Open AI, Co-Pilot... is not allowed unless specifically stated by the instructor. Students that are unsure about whether to use a particular technology should contact the instructor.”

Experienced teachers often find students ask the same questions. An effective tool to reduce ongoing time spent answering these questions is by simply providing students with a list of frequently asked questions. Even if students do not take the time to read this at the start of the course, the instructor can refer the student to it instead of repeating the same answers repeatedly. It is certainly true that providing detailed explanations of common student questions, outlining generative AI permissibility, establishing study tables ... will take initial efforts in set-up and organization, but they are effective at aiding student learning and will certainly pay off in reducing the ongoing time the instructor spends individually answering student questions.

Method and Depth of Instruction

The method(s) and depth of instruction employed are also important to enhance teaching efficiency. In general, it has been found that instructors should focus on covering less vs. more material. The amount of material covered has been found to be inversely related to the number of topics a student can grasp and retain. Weimer (2006), for example, finds that for any class or study session focusing on fewer topics allows students to learn more material. Particularly in courses instructed in-person, class time is often spent more efficiently if the instructor spends more time on fewer topics. This will then free up time to engage the students more productively through in-class discussions and activities. The quantity of material students learn in the course is not necessarily being reduced. The efficiencies arise from the focus on topics most critical to the course learning objectives and those topics that are more difficult for students to learn independently. It is ineffective and inefficient to attempt to touch on

every topic covered in a textbook. Many concepts can be readily understood by students, and if they are not, they can be encouraged to ask for clarification. Devoting class time, (lecture, review, or practice) on easy concepts not only reduces the time available to be spent on more difficult material, but students will be bored and pay less attention during class. This will also reduce student class attendance if students view class time as unnecessary or not helpful. Lecture topics should therefore be reserved for the most important and difficult material and in class activities should provide opportunities for students to practice and struggle with these concepts. It is likely that instructors will need to explain early in the course that they are only going to focus class time on the most difficult and important material. Further, it is helpful to point out that just because a topic is not presented in class does not mean that the students do not need to understand this topic and then clarify how it would be a waste of their time to cover many topics that are straight forward and easily understood. Certainly, courses taught in a hybrid or online format will also benefit from focusing on fewer topics more deeply. In these formats, the ancillary materials will take a larger role in focusing students on these more difficult topics. Efficiency is attained by focusing not on the topics which students already know, but on those that are most important and new, allowing for efficient use of class time.

Assessment and Feedback

Assessment and feedback can also be structured to allow for teaching efficiencies. Assessment should align with the course material and the practice and/or low-stakes homework and other activities that students are regularly assigned. For example, students could be assigned weekly multiple-choice quizzes and class time could be set aside for students to answer essay type practice questions. Particularly in hybrid and online courses where assessment is often conducted online, it is appropriate for instructors to use the same multiple choice test bank and similar essays for student course assessment. It will take considerable frontloading time to acquire enough questions, but once these test banks are set up, they can be used for every class taught going forward. Having a large test bank of assessment questions ensures students are not able to effectively cheat by sharing their work (since each student will receive completely different questions). A large test bank of questions will also free instructors to

provide plenty of sample questions that can provide low stakes feedback to students.

Teachers can also utilize Generative AI such as ChatGPT, Open AI, MetAI, Co-Pilot, Gemini ... to quickly provide an unlimited number of questions of any type, which the instructor can then select and/or modify. The key to receiving questions that are appropriate is to provide prompts that are specific to the type of question, the topic being assessed and the level of difficulty being assessed. For example, simply asking ChatGPT to provide a test question on "What is an Opportunity Cost?" It will yield various questions from simple definitions to more complex questions involving specific situations or numerical calculations. Although this variety might be appropriate, particularly for low stakes practice or homework, to better assess students' understanding, use a more specific prompt. For example, a prompt such as "Write a multiple-choice question with four answers that calculates the opportunity cost of buying something." will provide questions that force the student to apply the concept to a situation. To obtain even higher order question types add "challenging" or for less puzzling questions add "straight forward" to the prompt. For example, ask, "Write a challenging multiple-choice question with four answers that calculates the opportunity cost of buying something." After you receive a suitable question then simply ask, "Provide 5 additional versions of this question." Additionally, if you want to provide students with feedback then simply ask, "Explain why the correct answer provided is true and why the other options are incorrect."

Feedback has been found to play a significant role in student learning. Using a meta-analysis of 435 studies of feedback, Wisiewski et al. finds that feedback positively improves student learning. (Wisiewski, Zierer & Hattie 2020). Specifically, their studies find that feedback which contains more information is significantly more effective in positive learning outcomes and that corrective type of feedback is highly effective for learning new material. Hattie and Timperley (2007) find that three types of feedback are all important. "Feed-up" focuses on letting students know where they currently stand relative to the learning goals, "feed-back" provides students with how they have improved relative to their previous performance, and "feed-forward" guides students on how they can adapt their learning approaches to perform better in the future. This last type of feedback emphasizes how self-regulation is important in student learning. Empowering students to be responsible for their learning will go far in

increasing the efficiency of instruction. Guiding students on effective study strategies will give them the ability to perform better in the current (and future) course(s). One way to empower students to be better learners is to instruct them that re-reading and highlighting the textbook is less effective than self-testing their understanding of a section of the course material. One way to accomplish this is for students to simply progress through the textbook pausing and writing everything they know about a topic they just read. Alternatively, they can try explaining how one concept leads to the next concept anticipating what comes next in the textbook. Another efficient technique for in-person courses is to match students early in the course with a “study friend.” They can be encouraged to work with fellow students on activities throughout the course, studying together and quizzing each other on the topics. Generative AI can also be used effectively by students to self-test.

Feedback to students on essays or how they are progressing can be time-consuming. A worthwhile tool that can reduce the time of providing feedback is a text expander. There are many of these programs available, often providing free to use basic operations or trial periods. Phrase Express is a solid example of a text expander program that allows instructors to create “phrases” that can be inserted in online feedback boxes or emails to students. The “phrases” can be specific to commonly missed topics and blanks can be filled in with responses tailored specifically to the student. For example, if there are a few commonly made mistakes students make on an essay question a “phrase” can be inserted into the grading feedback box that provides help for that specific mistake. This approach can also save time by providing individualized student feedback on course performance after their midterms. Two “phrases” could be created. For the “A” students, the instructor could use a “phrase” that says, “_<student name>____, your performance at the halfway point of this course has been solid. Your homework average is _<hw>__, your write-ups average is _<writeup>_ and your current course grade is a <grd>__. Keep up the good work!” A key stroke would invoke this “phrase” and will prompt the instructor to type in only at the blanks. For the “D” student an alternative “phrase” could read, “_<student name>_, in reviewing your grades at the halfway point of this course, it appears you are really struggling. Your homework average is _<hw>__... I’d like to point out some resources that might help you going forward... Please feel free to contact me if you have any questions about any of the material covered or concerning this course in general.” A few

keystrokes will paste either of these “phrases” so instructors need only fill in the blanks while looking at a gradebook. Using similar “phrases” can handle any common correction or commonly asked question that then can be customized to fit the specific student situation. These “phrases” can be inserted in an email or any place where typing is performed.

Ancillary Materials

The use of appropriate ancillary materials can support the Course Design and Method of Instruction as discussed previously. Use of these materials will enhance teaching efficiency by reducing instruction time and allowing students to learn the material more efficiently. These materials are particularly important in hybrid and online courses which often do not have synchronous lectures as part of the course. The main goal in providing these is to enhance the material found in the textbook and provide opportunities for the student to practice their understanding. Since not all the course material that students are expected to learn is covered during class meetings, it is helpful to provide students with resources beyond the textbook.

One way to do this is to make small additions to a Power Point that asks the student to consider alternative examples or to answer questions over the concepts just presented. This allows for some interaction with the material that will enhance learning. It is also not difficult to construct multiple choice questions within a slide that will prevent the student from advancing until they answer correctly (and will send them backwards to the appropriate topic when they answer incorrectly). Once one of these type questions is designed, the series of slides can be readily re-used by changing only the question/answer text.

AI can also be used to quickly develop materials to provide students with step-by-step explanations of complex problems, labs or calculations. For example, asking a generative AI program to, “Write a step-by-step solution of the substitution and income effects when price increases and the good is inferior,” provides an example and five step process to solve this problem. The response even provides a summary at the end to reinforce how it arrives at the solution and goes on to highlight how the inferiority of the good is important to the correct solution.

On a cautionary note, the answers and explanations are not always correct. In one instance, when this substitution and income effects question was asked to Meta AI, the answer provided was the opposite of what is

true. Instructors should carefully read any AI responses and should caution their students about this possibility if they are using it to study on their own.

Videos are another efficient way to expose students to material. Students are likely less than enthusiastic to view full course length videos of past class meetings. Instead, short videos (less than 10 minutes) that focus on specific topics are more effective by providing readily available help to address student specific needs. Students are more willing to watch these since they are not forced to spend excessive time on topics they already understand. Listing an appropriate video title that includes the specific of topic(s) covered and the time length of the videos is also extremely helpful by directing students to the material they do not understand and letting them how much time they will need to allocate to view it.

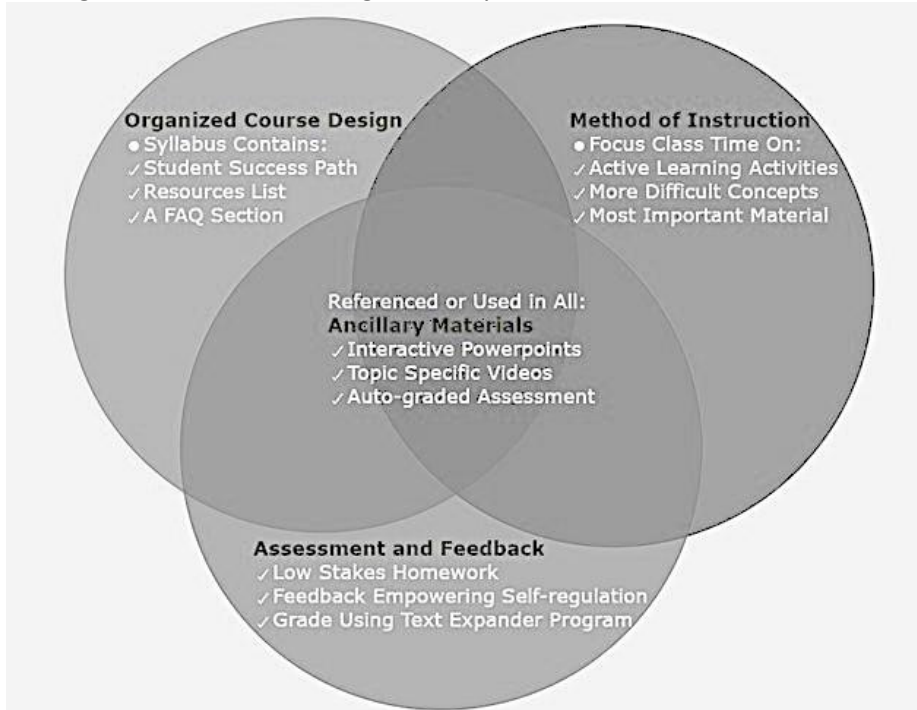
Sample or practice assignments that align with the types of questions used in assessment are also important. Most textbooks have homework platforms available that will allow students to practice their understanding. An alternative that is not tied to a specific publisher is Cerego. Cerego is an online homework platform that allows students to practice their understanding of course content by answering questions using a proven method of learning. It has content available that is applicable to many subjects and can be customized to the specific material needs of any specific course or textbook. Cerego allows students to do short study sessions from their phone and forces students to pace their learning over time. This type of spaced work has been found to be important for efficient learning (Kapler et al. 2015, Brown et al. 2014).

Conclusion

Higher education instructors are increasingly under pressure to teach more courses and improve learning outcomes. It is therefore more important than ever to teach efficiently. Modifying how courses are designed and taught can not only reduce the ongoing time demands but can enhance student learning. This paper outlined several strategies that will help instructors become more efficient (*Figure 1* summarizes the interrelation of these strategies), but there are certainly many more. It is unlikely that every suggestion outlined here is applicable to any course or instructor, but it is certainly true that efficiency gains will not come unless changes are made. Keeping the goal of improving efficiency at the forefront of the mind, being willing to try new approaches, and seeking and being

open to others' ideas and approaches are the keys to improving teaching efficiency.

Strategies Involved in Teaching Efficiency



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A Case Study of a College Algebra Co-Requisite Pilot: Exploring Student Perceptions

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The purpose of this case study research project was to examine student perceptions of a redesigned College Algebra co-requisite pilot course at a Mid-Western University. A group comprised of mathematics teachers from two of the University's regional colleges developed a co-requisite College Algebra design to develop student content and study skills and address concerns for student success and retention goals. This paper describes students' perceptions and how the co-requisite design impacted student outcomes. This case study focused on three research questions: 1) What are student perceptions of a co-requisite and College Algebra experience? 2) How are students' perceptions and participation in open access co-requisite College Algebra supplementary review sessions relevant to their mathematics learning, persistence, and achievement? 3) How do teachers perceive effectiveness of co-requisite support activities and student engagement and persistence? To investigate these questions, for fall 2023 and spring 2024 semesters, student participants enrolled in the pilot co-requisite College Algebra and CO-REQ supplementary review sessions provided feedback via surveys and their teachers submitted reflective observations. Themes that emerged from the qualitative analysis relate to student characteristics, co-requisite design aspects that are viewed as beneficial, barriers related to format and equitable access, and outcomes that indicate the supplemental course was helpful for students.

Nationally, over 59% of incoming students at two-year colleges are placed at a remedial course work mathematics sequence (Chen et al., 2016). The pandemic has only heightened concerns on student learning slide and a

potential “COVID crash” (Mangan, 2021) that may create more obstacles for student preparedness for college. To address college readiness concerns, multiple studies have applied a co-requisite mathematics model as an alternative pathway to developmental education (Andrews & Tolman, 2021) as an approach to issues with low retention rates and low graduation rates associated with developmental remediation at two-year colleges (Logue et al., 2019). Existing studies tend to emphasize quantitative aspects of predictors of success, focus on academic success and completion, and emphasize *non*-STEM (Science, Technology, Engineering, and Mathematics) based courses such as quantitative literacy and statistics (Andrews & Tolman, 2021; Boatman, 2021; Clinkenbeard, 2021; Logue et al., 2019). There is a paucity of studies that explore qualitative student perceptions regarding STEM-based College Algebra co-requisite courses. There are few studies that focus on students enrolled in Mid-Western STEM-based open-access College Algebra co-requisite courses.

This qualitative case study adds to existing research by exploring student perceptions of STEM College Algebra co-requisite experiences at Mid-Western regional colleges, and how students’ engagement in these courses are relevant to student persistence and achievement. This project uses Vygotsky’s (1978) Socio-Cultural Theory as a mathematical pedagogical approach to scaffold student learning and focus on learners as active participants. Astin’s (2012) Input-Environment-Outcome model is used as a theoretical framework to analyze perceptions of co-requisite teaching and learning approaches and context (Andrews & Tolman, 2021) and to consider learner input, teaching environment, and learner outcomes. To investigate College Algebra co-requisite experiences from students’ perspectives and understand factors that address student motivation and success, three main research questions were explored:

- 1) What are student perceptions of a co-requisite and College Algebra experience?
- 2) How are students’ perceptions and participation in open-access co-requisite College Algebra supplementary review sessions relevant to their mathematics learning persistence, and achievement? and
- 3) How do teachers perceive effectiveness of co-requisite support activities and student engagement and persistence?

The research questions and small class sizes led to choosing a qualitative case study design. The research design sought to humanize the co-requisite experience and give voice to students pursuing educational achievement. Students enrolled in either fall 2023 or spring 2024 semester open access redesigned co-requisite College Algebra and supplementary review sessions were given the opportunity to participate in this study. As part of normal class requirements during the semester, all students completed reflective assignments on study skills, critical thinking skills, and topics relevant for College Algebra skills. Their feedback was captured via pre-and-post surveys that each consisted of eleven questions on their mathematics content preparation and learning process. Survey questions captured details on demographics, Likert-based 5-point scale questions on mathematics identity and course perceptions, and open-ended questions on insights of course environment.

This paper discusses a summary of the literature on existing co-requisite mathematics studies and the study's choice of theoretical framework, design methodology applied for data collection instruments and plan, researchers' positionality statements, data analysis implementation plan, and an overview of findings. A discussion of the study outcomes and recommendations for future studies on STEM-based College Algebra co-requisite is provided.

Literature Review

This research study is set in two open-admission, open-access regional colleges of a Mid-Western university. Regional colleges are two-year colleges that are part of four-year colleges and offer low-cost options, smaller classes, and individualized resources to develop skills to "participate meaningfully in local communities" (Kisker, et al., 2016, p. 316). Open-admission and open-access regional colleges have nonselective admission policies and embrace access to democratic participation by enabling every applicant who has completed high school or a GED to access higher education opportunities and focus on ensuring preparation of underprepared students to enable this access (Scherer & Anson, 2014). Two-year community colleges historically serve underserved and underrepresented groups and provide an option to pursue university and career opportunities (Kisker et al., 2016). Typically, two-year college student representation includes students who are first-generation college attendees, from lower socio-economic status communities, and diverse linguistic, racial, ethnic, and cultural communities. Regional colleges have

the role of meeting the needs of diverse students and addressing college preparedness.

Unfortunately, traditional approaches to provide student support include remedial mathematics course sequence which are meant to bridge gaps and target increased student success but fail to address retention and completion (Childers et al., 2021; Douglas et al., 2023). Support required from administration and instructors is exacerbated by the effect of post pandemic on first-year college students' preparation for mathematics (Schwartz, 2023). Existing research explores alternate remediation and pathways for students that require developmental math sequence and the effects on student success and completion (Childers et al., 2021; Ragsdale et al., 2021). Alternate pathways include summer bridge course work, compressed remediation, and co-requisite mathematics that provide support during college-level course work as a substitute for remedial mathematics course sequence (Logue et al., 2019).

Student College Readiness Support: Co-Requisite Mathematics

Research findings on redesigned course "just in time" supplemental workshops and sessions indicate improvements for student completion and success for students in mathematics courses that apply accelerated delivery or co-requisite design (Boatman, 2021). Richardson and Dorsey (2019) explain co-requisite design considerations and provide recommendations for design. Andrews and Tolman (2021) study on co-requisite mathematics review existing research studies from Louisiana, California, and Tennessee and explain that co-requisite mathematics model set as a pass/fail course paired with college-level required math classes serves as an effective alternative pathway compared to traditional developmental education. Their research also points out studies' limitations and lack of details on how to develop academic interventions and lack of focus on STEM course work (research findings focus on non-STEM mathematics courses such as quantitative literacy and statistics as courses that align with students' major/career interests).

Logue et al. (2019, p. 300) reminds educators and administrators that "a demonstrated knowledge of the remedial course material was not particularly beneficial to students' subsequent college success," and their research analyzes quantitative literacy and statistic courses. Clinkenbeard's (2021) research on quantitative literacy co-requisite considers equity as an aspect of co-requisite courses that avoid deficit mindsets on student shortcomings. Co-requisite mingling with for-credit college mathematics

provides metacognitive motivation. An equitable asset-based constructivist epistemology that focuses on student active participation led to choosing Vygotsky's (1978) Socio-Cultural Theory (SCT) and Astin's (2012) Input-Environment-Outcomes (IEO) theoretical framework for this study.

Theoretical Framework: Vygotsky's SCT and Astin's IEO

This project's College Algebra course design applied Vygotsky's SCT and Zone of Proximal Development for mathematical pedagogical approach to scaffold student learning. Student interaction and class collaborative activities were central to mathematical meaning-making. Teachers scaffolded the supplemental review sessions but emphasized student construction of knowledge. Student background knowledge and cultural tools for learning align with Astin's IEO theoretical framework that considers participant background, characteristics, and interests as an input aspect to learning, the college learning environment factors that influence student learning, and outcomes of this teaching and learning environment (Andrew & Tolman, 2021).

Methodology

This study's research purpose focuses on concerns for student motivation and persistence in STEM-based mathematics College Algebra courses. This study applies a qualitative case study approach to explore student perceptions of a College Algebra co-requisite redesign pilot course at two regional campuses in a Mid-Western university setting. The three research questions focus on 1) What are student perceptions of their experiences in the College Algebra co-requisite pilot; 2) How are students' perceptions and participation in open-access co-requisite College Algebra supplementary review sessions relevant to their mathematics learning, persistence, and achievement; and 3) How do teachers perceive effectiveness of co-requisite support activities and student engagement and persistence? Yin (2009) states a case study's research questions pose the "'who,' 'what,' 'where,' 'how,' and 'why' questions" (p. 9) and are a research approach that has two elements: an investigation of real-world phenomenon, and a clear context and boundary (p. 15). The researcher's choice of a case study is based on investigating student perceptions of experiences in co-requisite STEM-based College Algebra which is a current approach to improve student retention and success in mathematics. Why this matters is this focuses on student success and persistence in an open-access Mid-Western college environment which caters to underrepresented

and underserved students who overrepresent first-generation and low-income status. This study's research questions pose the *what* and *how* question forms to explore student perceptions and understand outcomes to add to current co-requisite research conversations.

Although initial research investigator intentions were to use a mixed-method approach, the small number of students in College Algebra co-requisite classes consisting of a maximum of 25 students per class for a total of three instructors resulted in supplemental review sessions that comprised of three to six students per semester for a total of three supplemental classes at both regional colleges. A qualitative research approach is appropriate for this study that explores student persistence, motivation, and success with a co-requisite STEM-based College Algebra intervention to understand student experiences, insights, and perspectives and interpret implications of findings (Creswell & Guetterman, 2019).

Participants and Setting

This project involved a group of five mathematics professors from two Mid-Western university regional sites. Three members of the group identify as White, one as Middle Eastern, and one as Latina; two are male professors and three are female professors. For the first year of the two-year project, the group had meetings that included department chairs and STEM professors who shared active-learning teaching approaches and experiences with co-requisite mathematics. During the second year, annual year 2023-2024, the co-requisite pilot was completed by three of the five mathematics professors in the group, and the remaining two served as co-principal investigators. One diverse suburban regional site, College A, has student ethnicity representation of 64% White, 26% underrepresented minorities (Black or African American, Hispanic or Latino, and two or more races), 5% Asian, 2% unknown race/ethnicity, and 2% non-resident alien (US News, 2024). The other rural regional site, College B, has student ethnicity distribution of 74% White, 15% underrepresented minorities, 3% Asian, 6% unknown race/ethnicity, and 2% non-resident alien (US News, 2024).

The university Institutional Review Board granted approval for this research study to be conducted at both regional sites during fall 2023 and spring 2024. Only students enrolled in the redesigned co-requisite College Algebra classes and its optional supplementary research sessions (SRS, CO-REQ) at either of the two regional sites were invited to participate in the study. Students who enrolled in the three-credit co-requisite redesigned College Algebra course had the option to take an optional one-credit CO-

REQ class. The co-requisite College Algebra professors encouraged students who were struggling during the first two weeks to enroll in the CO-REQ class, and two of the three mathematics professors had students enroll in the co-requisite CO-REQ classes. One professor taught College Algebra in a hybrid format, and the CO-REQ was taught as a face-to-face in person class; and the other professor taught both College Algebra and the CO-REQ in Hyflex format.

The authors/researchers of this paper, including two co-principal investigators from the group, were engaged in the recruitment process, and adhered to IRB guidelines. The co-requisite course professors included an invitation to the research study in their course Learning Management System. To prevent any conflict of interest, the authors/researchers administered consent forms to students when the course professors were not present. Student participants include a total of eleven students, pseudonyms are shown in Tables 1 and 2, enrolled in both co-requisite CO-REQ and redesigned pilot College Algebra classes for fall 2023 and spring 2024, and a total of eleven students enrolled only in the co-requisite redesigned pilot College Algebra classes for fall 2023 and spring 2024 semesters. Student participants are listed in the attached table (see Table 1 and Table 2). All participant names listed are pseudonyms, to adhere to IRB confidentiality.

Table 1: *Co-requisite College Algebra and CO-REQ Participants*

Semester	Participant	College Algebra Course Format	CO-REQ Format	Demographic Identity	Open-Access Mid-Western Regional College
Fall 2023	Camila	Hybrid	In-person CO-REQ	White Female	College A
	Aria	Hybrid	In-person CO-REQ	Black/African American Female	College A
	Henri	Hybrid	In-person CO-REQ	White Male	College A
	Luna	Hybrid	In-person CO-REQ	Hispanic Female	College A
	Joe	Hybrid	In-person CO-REQ	Unknown	College A

	Amy	Hyflex	Hyflex CO-REQ (attended all online)	White Female	College B
	Rory	Hyflex	Hyflex CO-REQ (attended mostly in-person)	Unknown	College B
	Rachel	Hyflex	Hyflex CO-REQ (attended half online, half-in-person)	White Female	College B
	Brian	Hyflex	Hyflex CO-REQ	White Male	College B
Spring 2024	Elijah	Hybrid	In-person CO-REQ	African American Male	College A
	Jacob	Hybrid	In-person CO-REQ	White Male	College A

Table 2: *Participants enrolled only in Co-requisite College Algebra*

Semester	Participant	College Algebra Course Format	CO-REQ Format	Demographic Identity	Open-Access Mid-Western Regional College
Fall 2023	Teri	Hybrid	Not enrolled	Unknown	College A
	Hadaya	Hybrid	Not enrolled	Unknown	College A
	Fran	Hybrid	Not enrolled	Unknown	College A
	Sol	Hybrid	Not enrolled	Unknown	College A
	Jin	Hybrid	Not enrolled	Unknown	College A
Spring 2024	Destiny	Hybrid	Not enrolled	White Female	College A

	Ethan	Hybrid	Not enrolled	White Male	College A
	Liam	Hybrid	Not enrolled	White Male	College A
	Genet	Hybrid	Not enrolled	Unknown	College A
	Guozhi	Hybrid	Not enrolled	Asian Male	College A
	Nina	Hybrid	Not enrolled	Multi-racial Female	College A

Data Collection Procedures and Instruments

To explore student perceptions of experiences in the CO-REQ and College Algebra courses, data artifacts included student pre-and-post surveys and teacher reflections of student engagement with topics that address content and study skills. In addition to surveys that professors administered as part of normal course work, student participants were given the option to participate in optional focus group interview sessions which could be done online or in-person.

The pre-and-post-surveys (see Attachment A) administered to students consisted of ten to eleven questions. The pre-survey contained demographics questions, and six Likert-scaled (five-point scale) questions focusing on mathematics identity, and perceptions of experiences in the math course. College Algebra students were also asked if they registered for the CO-REQ and the reason for enrolling or not enrolling in that class. The post-survey contained the same six Likert-scaled questions and five open-ended questions focusing on aspects of the co-requisite and College Algebra course that were helpful or could be improved.

Not all students submitted both a pre-and-post survey, and since the surveys administered in College B had a variation of the IRB-approved Likert-scaled questions, these Likert responses could not be included for data analysis. A total of four pre-and-post submissions collected were valid for analysis of Likert-scaled responses. A total of seven pre-survey open-ended responses had student submissions for the question “Did you register for supplemental corequisite MATH1096, if yes state why you chose to do so, and if no state why you did not choose to participate in that course?” (two enrolled in both College Algebra and CO-REQ, and five in only College Algebra). A total of 16 post-survey open-ended responses were submitted

by students (nine students enrolled in both College Algebra and CO-REQ, and seven enrolled only in College Algebra). No students engaged in interview sessions (see Attachment B).

The two mathematics professors for College Algebra and CO-REQ courses, from the two regional sites, completed reflective responses to pre-defined prompts (see Attachment C). Each professor provided at least two reflections that addressed the start of the semester and later in the semester. Only one professor assigned to the pilot College Algebra and CO-REQ course submitted reflections for the spring 2024 semester. The second professor from College B taught the courses but did not have any student consent for spring semester to participate in the research study.

Data Analysis Process

Data analysis was conducted by the three authors, who also served as researchers. The participant responses to open-ended pre-and-post survey prompts were reviewed separately by each of the researchers to ensure internal validity of qualitative analysis. The three researchers applied triangulation of the data sources by comparing student pre-survey, student post-survey, and professor reflections that spanned the semester. Two of the three researchers were part of the original group and referred to prior meetings and emails related to the study. The third researcher joined the team post data collection.

All three researchers analyzed qualitative data according to Austin's Input, Environment, Outcomes Apriori themes. Each researcher reviewed the pre-survey and post-survey participant responses and noted Input, Environment, and Outcome descriptive codes. Miles et al. (2020) describes descriptive codes as short phrase labels that capture the essence of a particular passage and are well aligned to non-interview setting. In Vivo coding was also used to honor the voice of participants to ensure themes are portrayed that exhibit participant voice and views. All three researchers then collectively reviewed themes to triangulate findings.

In addition to qualitative data analyses, a basic mean and median calculation was used to explore participant responses to the six posed Likert scale questions. Both the pre- and post-survey used slight variations of the same six Likert scale questions. The pre-survey questions were worded to note participant responses before completing their semester coursework. The post-survey questions had tense changes to refer note participant responses after completing their semester coursework (See Attachment D). The questions addressed student confidence with their mathematics skills.

Teacher reflections are analyzed based on Vygotsky’s (1978) SCT teaching framework for student group work, discussion, and instructor scaffolding.

Results: Themes

Analysis of the student and professor data artifacts resulted in themes related to students’ perceptions of their CO-REQ experiences. Results will be presented in alignment with the research questions. Five themes emerged for the first research question, two themes emerged for the second research question, and two teacher perspectives are relevant for the third research question.

Themes for Research Question 1

The first research question stated: What are student perceptions of a co-requisite and College Algebra experience? Descriptive statistics relevant to student responses for the Likert-scaled questions are discussed first, and then data analysis outcomes related to qualitative open response questions are provided. Four students from the CO-REQ course completed both the pre- and post-survey. For each of these survey questions, the mean value increased from the pre-survey to the post-survey, indicating improved comfort level and confidence in their mathematics abilities (see Table 3).

Table 3: *Pre- and Post-Survey Likert responses*

Student	Q1		Q2		Q3		Q4		Q5		Q6	
	Pre-Survey	Post-Survey	Pre-Survey	Post-Survey	Pre-Survey	Post-Survey	Pre-Survey	Post-Survey	Pre-Survey	Post-Survey	Pre-Survey	Post-Survey
Mean	2.75	3.25	3.5	4	2.75	3.75	4.25	4.5	3.25	3.5	3.25	4
Median	3	3	3	4	2.5	3.5	4	4.5	3	3	3.5	4

For qualitative analysis of students’ responses to open-ended questions, we applied Astin’s I-E-O framework, and five themes emerged relevant to input and environment details. The five themes include 1) Integrity and initiative; 2) Homework is helpful; 3) CO-REQ peer problem solving is beneficial; 4) CO-REQ students value opportunities to receive help and ask questions; 5) Concerns with Hybrid/Hyflex format.

One theme that emerged relative to Astin’s input characteristics is student integrity and initiative. Limited information was shared by students pertaining to input details such as student backgrounds, but student comments show that students had a willingness to take initiative and

expressed a dedication to wanting to be successful in their course experience. All students from the CO-REQ revealed initiative and discussed extra class time and dedication to study and practice. Students who were only in the College Algebra course were also dedicated to class preparation, and their comments focused on external resources and preparation. The next four themes are pertinent to Astin's environment aspects.

Both CO-REQ and College Algebra students found homework helpful. Nina, Rory, Sol, Fran, Hadaya, and Luna commented that the homework was the most helpful aspect of their course experience. This shows these students valued the assigned homework questions as time to work on and refine their computational skills. Hadaya, and Fran from the College Algebra section stated they needed to dedicate extra time to search for external resources to review for homework.

CO-REQ peer problem solving is beneficial to students, and Aria commented "having my peers help me," as an important aspect of the supplemental sessions. Elijah wrote that "it is helpful to get input on how to get the problem solved from your peers." The CO-REQ teachers implemented an environment to scaffold student questions and emphasized student peer-to-peer interaction as active participants, and students who registered for the course worked well in this setting.

CO-REQ students value opportunities to receive help and ask questions from their professor during their extra session time. Elijah explained that "everything was broken down so you could understand," and Jacob said the interaction "really helps polish your skills." This shows students taking advantage of this scaffolding teaching and learning opportunity.

College Algebra students expressed concerns with Hybrid/Hyflex format. Genet, Nina, and Hadaya felt class time was insufficient, and Teri said, "it was difficult to do the assignment alone + stay up to date on information," and as a result she "did not get as much out of the course."

Themes for Research Question 2

The second research question stated: How are students' perceptions and participation in open-access co-requisite College Algebra supplementary review sessions relevant to their mathematics learning persistence, and achievement? Descriptive statistics relevant to student letter grades are discussed first, and then data analysis outcomes related to qualitative open response questions are provided.

For the fall 2023 semester, all students in the CO-REQ courses passed the course. One student in the Spring 2024 CO-REQ course did not pass, but the instructor commented that this student ceased coming and participating in the course early in the semester. For the nine CO-REQ student respondents who passed the supplemental one-credit course, data on two letter grades was not provided by the instructor for the College Algebra grades, but of the remaining 7 respondents, all passed College Algebra with a C- or higher (4 As, 1 B, 2 C letter grade range). For the student respondents who were only in College Algebra, one student withdrew from, and two students did not pass the College Algebra course. Grade details for the CO-REQ and College Algebra courses are shown in Table 4.

Table 4: *Course Grades*

Course Grades			
Semester	Course	Grade	Tally
Fall 2023	Math 1096 CO-REQ	Pass	7
		Not Pass	0
	Math 1021 College Algebra	A	2
		A-	2
		B	2
		B-	2
		C+	1
C-	1		
Spring 2024	Math 1096 CO-REQ	Pass	2
		Not Pass	1
	Math 1021 College Algebra	A	2
		A-	1
		B	1
		C	1
		C-	1
		W	1
NP	2		

Analysis of student responses to open-ended questions resulted in two themes based on Astin’s outcomes for I-E-O framework: 1) CO-REQ respondents recommend this course; 2) College Algebra respondents who wished to take CO-REQ had scheduling conflicts.

As an outcome measure, when asked if they would recommend the CO-REQ course to other students, CO-REQ students unanimously commented yes, they would recommend the course. Camila commented

“Yes. It is good to have a course made to help you better understand things.” According to Henry, “this course is a key component to success with math.” Amy and Rachel both commented that the course is helpful. All 9 CO-REQ respondents commented that the CO-REQ course was helpful, and all passed the CO-REQ course. Additional comments from participants emphasize the outcome themes expressed. Luna commented that they wished they could have taken the CO-REQ and College Algebra courses as a full in person course, instead of as an online course. Nina expressed dissatisfaction that there were “no in person lesson, just review” in the College Algebra course, and Camila commented, “It is good to have a course made to help you better understand things.”

Interestingly, even though instructors and researchers addressed the class multiple times and information regarding the CO-REQ was announced and shared via the course LMS, one student (Guozhi) commented they were not aware of the CO-REQ course. Two students wished they had extra help, and three students commented they were not able to take advantage of the CO-REQ course due to work conflicts or time conflicts. These conflicts speak to equity concerns regarding the CO-REQ separate schedule for students who have work and/or family constraints.

Themes for Research Question 3

The third research question asked: How do teachers perceive effectiveness of co-requisite support activities and student engagement and persistence? Instructors were asked to complete a reflection to share their insights relative to the CO-REQ course. One instructor commented that the students who self-enrolled in the CO-REQ course were high-performing students who “have strong math backgrounds and striving for an A in College Algebra. The expectation was that students would require support on math skills, but this group was high-performing and requested additional homework review.” This instructor went on to comment that the small group size “resulted in a deeper personal relationship” with the students. The second instructor commented that strong student peer-to-peer collaboration for group activities and review were a strength of the CO-REQ model. Their CO-REQ content focused on College Algebra topics including linear inequalities, exponentials, and logarithms. Interactive activities, which required pair and group discussions, began with instructor guidance and questions, and developed into student peer-to-peer engagement and support were commonly used to review CO-REQ topics. These interactive

activities promoted high levels of engagement, leaving students to request instructor assistance only when they feel "stuck."

Attendance was listed as a concern by both instructors. One instructor found that at one point only 2 of 6 students were attending the CO-REQ course. The two students in attendance were engaged and worked well. Both instructors also commented that the CO-REQ course did not play out the way initially intended. Prior to launching the CO-REQ course, instructors and researchers spent time developing activities to parallel the College Algebra curriculum and provide scaffolding support for struggling students. These resources were not implemented as in actuality the CO-REQ students were strong students who did not need additional support. One instructor commented that study skills, self-confidence in their mathematics ability, and time management skills were more of a conversation focus in the CO-REQ course.

Limitations and Implications for Future Direction

The CO-REQ course proved valuable to students but did not turn out as intended at the onset of this pilot project. Low enrollment was based on a small student enrollment number for each College Algebra class and student schedules not being able to mesh with an additional course time requirement. Signing up for CO-REQ as a separate course after the semester began did not prove to be a sustainable model. Students who did enroll in the CO-REQ course appreciated the instructors' taking time to cater CO-REQ sessions to student needs while promoting peer collaboration and providing resources, such as homework, to practice and hone skills.

Future studies are recommended as the need to explore ways to promote success in College Algebra continues to be a valuable topic. The research group from this study is next going to focus on offering a 4 credit College Algebra course that combines the CO-REQ and College Algebra experiences from this study into one course. With the additional time of a 4-credit course, the strengths of the CO-REQ course, such as focused time to work on problem-solving, teacher support, and peer collaboration, will be blended continuously into the College Algebra course experience.

Initially, this study was designed to have additional data collection measures through focus groups and interviews conducted with CO-REQ and College Algebra students. Disappointingly, no student participants responded as willing to participate in interviews or focus groups to further discuss their experiences. This lack of additional student voice data and the small sample size of this study are limiting factors.

The CO-REQ course proved valuable to students. Student perceptions of the co-requisite and College Algebra experience was the CO-REQ was valuable and provided good opportunities to engage with peers and instructors. Student participation in the CO-REQ courses was strong and grades reflected solid understanding of the College Algebra content. While the CO-REQ courses did not go as initially visualized, instructors found the time with students to be valuable and saw good participation and engagement amongst students.

Discussion

In summary, two-year open-access colleges continue to address the importance of students' preparation for college-level mathematics. This qualitative case study focuses on open-access College Algebra co-requisite courses at two Mid-Western regional colleges. Our purpose was to explore both student and teacher perceptions to consider student motivation, persistence, and achievement. The data collected and analyzed helped explore student perceptions of their experiences in the pilot CO-REQ learning environment, how their perceptions and participation are relevant to their math learning and achievement, and how teachers perceive the effectiveness of CO-REQ learning activities. Descriptive statistics reveal CO-REQ participants indicate an improved confidence in their math learning abilities, and, for this small number of students, the grade details are encouraging. Qualitative analysis outcomes indicate students in the CO-REQ section valued extra time to review questions, peer-problem-solving time, and recommend this course. Both CO-REQ and College Algebra students who were not enrolled in CO-REQ demonstrated dedication and integrity, and College Algebra participants concurred with CO-REQ peers that homework was helpful, but expressed concerns related to insufficient class time. This concern, combined with College Algebra student issues regarding CO-REQ separate schedule time constraints impacted the decision for future courses. College Algebra and CO-REQ will be offered as a 4-credit course to address equity access and scheduling concerns, while still promoting opportunities for deeper personal instructor-student and peer interactive classroom engagement. The findings are valuable for teaching-centered two-year college decisions on CO-REQ college algebra implementation to support students.

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Attachment A: Student Pre-and-Post Surveys

MATH 1096 (Corequisite support course for College Algebra) Pre-Survey:
If there are any questions you do not wish to answer please select/write “no response”

1. What is your age (under 18, 18-24, 25-34, 35 or more, or no response)?
2. What is your gender identity (female, non-binary/non-conforming, male, self-description, or if you prefer not to answer write no response)?
3. What is your racial or ethnic background (American Indian or Alaska Native, Asian, Black or African American, Multiracial, Native Hawaiian or other Pacific Islander, White, Self-description or no response)?
4. What is the last math class you have taken (be specific on subject and if high school or college level)?
5. On a scale of 1-5, how comfortable are you with mathematics?
 - 1 - Not at all comfortable
 - 2 - Slightly comfortable
 - 3 - Moderately comfortable
 - 4 - Very comfortable
 - 5 - Extremely comfortable
6. On a scale of 1-5, how confident are you in your ability to learn mathematics?
 - 1 - Not at all confident
 - 2 - Slightly confident
 - 3 - Moderately confident
 - 4 - Very confident
 - 5 - Extremely confident
7. On a scale of 1-5, how much do you enjoy learning mathematics?
 - 1 - Not at all enjoyable
 - 2 - Slightly enjoyable
 - 3 - Moderately enjoyable
 - 4 - Very enjoyable
 - 5 - Extremely enjoyable
8. On a scale of 1-5, how much do you think the supplemental math course will assist you in College Algebra?
 - 1 - Not at all
 - 2 - Slightly
 - 3 - Moderately
 - 4 - Very
 - 5 - Extremely
9. On a scale of 1-5, how much do you agree with the statement “I have the ability to do the skills required for College Algebra”?
 - 1 - Not at all
 - 2 - Slightly

- 3 - Moderately
- 4 - Very
- 5 - Extremely

10. On a scale of 1-5, how important do you think College Algebra is to your academic success?

- 1 - Not at all important
- 2 - Slightly important
- 3 - Moderately important
- 4 - Very important
- 5 - Extremely important

**MATH 1096 (Corequisite support course for College Algebra) Post-Survey:
If there are any questions you do not wish to answer please select/write "no response"**

1. How comfortable are you with mathematics now, after taking this course?

- 1 - Not at all comfortable
- 2 - Slightly comfortable
- 3 - Moderately comfortable
- 4 - Very comfortable
- 5 - Extremely comfortable

2. How confident are you in your ability to learn mathematics now, after taking this course?

- 1 - Not at all confident
- 2 - Slightly confident
- 3 - Moderately confident
- 4 - Very confident
- 5 - Extremely confident

3. How much do you enjoy learning mathematics now, after taking this course?

- 1 - Not at all enjoyable
- 2 - Slightly enjoyable
- 3 - Moderately enjoyable
- 4 - Very enjoyable
- 5 - Extremely enjoyable

4. How much do you think the supplemental math course helped you in College Algebra?

- 1 - Not at all
- 2 - Slightly
- 3 - Moderately
- 4 - Very

-
- 5 - Extremely
5. How much do you agree with the statement “I have the ability to do the skills required for College Algebra”?
- 1 - Not at all
2 - Slightly
3 - Moderately
4 - Very
5 - Extremely
6. How important do you think College Algebra is to your academic success now, after taking this course?
- 1 - Not at all important
2 - Slightly important
3 - Moderately important
4 - Very important
5 - Extremely important
7. What were the least helpful aspects of this co-requisite course?
8. What were the most helpful aspects of this co-requisite course?
9. What advice would you give to future students taking this co-requisite course?
10. Would you recommend this course to other students? Why or why not?
11. Do you have any additional comments you wish to share regarding learning strategies, practice, challenges, support, etc.?

MATH 1021 (College Algebra) Pre-Survey:

If there are any questions you do not wish to answer, please select/write “no response”

1. What is your age (under 18, 18-24, 25-34, 35 or more, or no response)?
2. What is your gender identity (female, non-binary/non-conforming, male, self-description, or if you prefer not to answer write no response)?
3. What is your racial or ethnic background (American Indian or Alaska Native, Asian, Black or African American, Multiracial, Native Hawaiian or other Pacific Islander, White, Self-description or no response)?
4. Did you complete any of the college developmental sequence prerequisite courses prior to this class, or did your math placement place you into this College Algebra class?
5. On a scale of 1-5, how comfortable are you with mathematics?
- 1 - Not at all comfortable
2 - Slightly comfortable
3 - Moderately comfortable
4 - Very comfortable
5 - Extremely comfortable

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6. On a scale of 1-5, how confident are you in your ability to learn mathematics?
 - 1 - Not at all confident
 - 2 - Slightly confident
 - 3 - Moderately confident
 - 4 - Very confident
 - 5 - Extremely confident
 7. On a scale of 1-5, how much do you enjoy learning mathematics?
 - 1 - Not at all enjoyable
 - 2 - Slightly enjoyable
 - 3 - Moderately enjoyable
 - 4 - Very enjoyable
 - 5 - Extremely enjoyable
 8. On a scale of 1-5, how prepared do you feel for College Algebra?
 - 1 - Not at all
 - 2 - Slightly
 - 3 - Moderately
 - 4 - Very
 - 5 - Extremely
 9. On a scale of 1-5, how much do you agree with the statement “I have the ability to do the skills required for College Algebra”?
 - 1 - Not at all
 - 2 - Slightly
 - 3 - Moderately
 - 4 - Very
 - 5 - Extremely
 10. On a scale of 1-5, how important do you think College Algebra is to your academic success?
 - 1 - Not at all important
 - 2 - Slightly important
 - 3 - Moderately important
 - 4 - Very important
 - 5 - Extremely important
 11. Did you register for supplemental corequisite MATH1096, if yes state why you chose to do so, and if no state why you did not choose to participate in that course?

MATH 1021 (College Algebra) Post-Survey:

If there are any questions you do not wish to answer, please select/write “no response”

1. How comfortable are you with mathematics now, after taking this course?

-
- 1 - Not at all comfortable
 - 2 - Slightly comfortable
 - 3 - Moderately comfortable
 - 4 - Very comfortable
 - 5 - Extremely comfortable
1. How confident are you in your ability to learn mathematics now, after taking this course?
 - 1 - Not at all confident
 - 2 - Slightly confident
 - 3 - Moderately confident
 - 4 - Very confident
 - 5 - Extremely confident
 2. How much do you enjoy learning mathematics now, after taking this course?
 - 1 - Not at all enjoyable
 - 2 - Slightly enjoyable
 - 3 - Moderately enjoyable
 - 4 - Very enjoyable
 - 5 - Extremely enjoyable
 3. How would you characterize your math skills preparation for College Algebra after taking this course?
 - 1 - Not at all prepared
 - 2 - Slightly prepared
 - 3 - Moderately prepared
 - 4 - Very prepared
 - 5 - Extremely prepared
 4. How much do you agree with the statement "I have the ability to do the skills required for College Algebra"?
 - 1 - Not at all
 - 2 - Slightly
 - 3 - Moderately
 - 4 - Very
 - 5 - Extremely
 5. How important do you think College Algebra is to your academic success now, after taking this course?
 - 1 - Not at all important
 - 2 - Slightly important
 - 3 - Moderately important
 - 4 - Very important
 - 5 - Extremely important
-

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6. What were the least helpful aspects of this College Algebra course?
 7. What were the most helpful aspects of this College Algebra course?
 8. What advice would you give to future students taking this College Algebra course (specifically, how should students prepare for this course)?
 10. If you registered for MATH1096 corequisite, would you recommend future students take that course to supplement College Algebra (please provide details on why or why not)?
 9. If you did not register for MATH1096, after taking College Algebra do you think you would reconsider and recommend future students take that corequisite course to supplement College Algebra (please provide details on why or why not)?
 10. Do you have any additional comments you wish to share regarding learning strategies, practice, challenges, support, etc.?

Attachment B: Student Focus Group Questions
Semi-Structured Interview Guideline (30-45minutes).

Thank you so much for volunteering to participate. We appreciate your opinions and input, and we are glad you are sharing your thoughts today. And if any question makes you uncomfortable you can choose not to reply and go onto another question.

1. How would you describe your “relationship” with mathematics? Prompts: do you enjoy it, appreciate it, fear it, etc.
2. How would you characterize yourself as a mathematics learner (good, nervous, etc.)
3. What do you think is important about mathematics?
4. Why do you think math is relevant or not?
5. How do you feel that math is related to you and your life?
6. What were your past experiences with math classes and compare that with current experience in MATH1021?
7. What has been your experience in MATH1096 (for those in the corequisite course)?
Prompts: What is helpful? What is a challenge? What support, if any, does the corequisite course provide?
8. If you are not in the corequisite Math 1096 course why did you choose not to be in MATH1096?
Prompts: Did you receive guidance/support from teachers/mentors/administrators in this choice? Did you feel support from family/friends/school on decision? After completing College

Algebra would you rethink option of registering for MATH1096 support class?

9. What has been your experience in MATH1021 College Algebra?
Prompts: What has been helpful, what has been a challenge? What would you recommend to support achievement?
10. How would you describe your mathematics ability prior to your current MATH1096 course and how would you describe your ability now? What changed (if applicable)
11. If you are in Math 1096, what do you like about the learning environment in MATH1096? What would you change or improve about the learning environment?
Prompt: How does MATH1096 prepare you or not for MATH 1021
12. What do you like about the learning environment in MATH1021? What would you change or improve about the learning environment?

Attachment C: Professor Reflection Prompts

1. Faculty Name
2. Topic(s) covered this week in Math 1021 (College Algebra Course)
3. Topic(s) covered this week in Math 1096 (CO-REQ Class)
4. Evidence of student engagement from this week.
5. What went well this week?
6. Did you have any issues or concerns with Math 1096 this week?
7. Do you have any observations regarding Math 1096 or Math 1021 from this week?
8. Additional Comments (consider any ethical issues, biases; reflect on different perspectives and approaches that you might wish to incorporate in the upcoming weeks)

Attachment D: Student Likert-Scaled Pre-and-Post Questions

Pre-Survey

1. How comfortable are you with Mathematics?
2. How confident are you in your ability to learn Mathematics?
3. How much do you enjoy learning Mathematics?
4. How much do you think the supplemental math course will assist you in learning College Algebra?
5. How much do you agree with the statement "I have the ability to do the skills required for College Algebra"?
6. How important do you think College Algebra is to your academic success?

Post-Survey

1. How comfortable are you with Mathematics now after taking this course?
2. How confident are you in your ability to learn mathematics now, after taking this course?
3. How much do you enjoy learning mathematics now, after taking this course?
4. How would you characterize your math skills preparation for College Algebra after taking this course?
5. How much do you agree with the statement "I have the ability to do the skills required for College Algebra"?
6. How important do you think College Algebra is to your academic success now, after taking this course?

A Case Study on Using AI to Optimize Instructional Quality and Administrative Efficiency: A Practical Approach for Regional Campuses

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This study explores the innovative use of AI language models, specifically ChatGPT, to enhance both teaching and administrative efficiency in General Chemistry courses at a regional campus. By integrating AI tools, faculty can streamline course preparation, support personalized student learning, and significantly reduce the time spent on routine administrative tasks. The study highlights practical applications of ChatGPT, including the development of scaffolded worksheets that break down complex chemistry topics, the creation of multi-version assessments to support Specifications Grading (Specs Grading), and the inclusion of real-life chemistry examples to increase student engagement. While this study focuses on ChatGPT, the findings have broader implications for the adoption of various AI models in similar educational and administrative contexts.

Data collected from three semesters demonstrates a notable increase in student quiz scores, with an average improvement of 3.5 points after the implementation of AI-generated learning materials. Student feedback collected through Likert-scale surveys showed high satisfaction, with scores averaging 4.5 out of 5 for the clarity and usefulness of AI-generated worksheets. Additionally, ChatGPT assisted in administrative tasks, such as drafting detailed letters of recommendation and summarizing departmental meetings, contributing to about 30% reduction in time spent on these tasks.

These findings suggest that ChatGPT not only enhances student comprehension of challenging topics but also helps faculty manage their workload more efficiently. This study provides actionable insights and a model for other regional campus faculty to leverage AI in ways that improve both teaching quality and operational efficiency, making it a valuable resource for educators seeking practical solutions to common challenges in higher education.

Introduction

The integration of artificial intelligence (AI) in educational settings has shown promise in addressing these challenges by enhancing both instructional and administrative efficiency. Research indicates that AI tools can support educators by automating routine tasks, such as grading, creating personalized assessments, and organizing data, allowing faculty to devote more time to direct student interaction (Guan et al., 2020; Woolf, 2010). In particular, AI-driven tools like intelligent tutoring systems have been found to reduce the time required for feedback and assessment while providing personalized learning experiences tailored to students' individual needs (Murtaza et al., 2022; Nye, 2015). AI's potential to streamline administrative duties, such as drafting recommendation letters or summarizing meeting notes, further contributes to time savings and workload management for faculty, especially in settings where instructors balance high teaching loads with service responsibilities (Holmes et al., 2019; Bates & Sangrà, 2011). As West (2018) notes, the ability of AI to automate repetitive tasks has transformative implications for higher education, potentially reshaping how faculty allocate time and resources.

Faculty at regional campuses often face the unique challenge of balancing high teaching loads with diverse administrative responsibilities, making efficient time management essential. In addition to classroom instruction, these faculty members are responsible for tasks such as creating detailed lesson plans, managing grading systems, writing recommendation letters, and participating in committee work. These demands can limit the time available for developing innovative teaching strategies or providing individualized feedback to students. Although recent studies have highlighted AI's potential in educational settings, there is limited research focusing specifically on regional campuses, where faculty navigate a distinctive blend of instructional and administrative duties. These campuses also attract diverse student populations, including recent high school graduates, mature students, returning students, and individuals changing careers, each with varied learning styles and levels of academic preparedness. This diversity makes personalized and adaptive learning materials crucial for effective instruction. Balancing high teaching loads with administrative responsibilities leaves limited time to meet these diverse learning needs effectively. Addressing this gap, this study investigates how AI, specifically ChatGPT, can support regional campus faculty by improving

time efficiency, enhancing instructional quality, and reducing administrative workload.

One instructional tool that has proven effective in promoting student understanding is the scaffolded worksheet. Scaffolded worksheets, which guide students through progressively challenging concepts, have been shown to enhance comprehension and build foundational knowledge in various subjects, including chemistry (Clark & Mayer, 2016; Reiser & Tabak, 2014). Research indicates that scaffolded learning materials can help students achieve deeper understanding by breaking down complex concepts into manageable steps, making it easier for students to develop the skills needed to tackle advanced topics (Wood et al., 1976). However, creating personalized and adaptive scaffolded worksheets for individual students or different learning groups can be time-consuming. Here, AI offers a significant advantage by efficiently generating multiple versions of scaffolded worksheets tailored to students' unique needs, enabling more personalized learning experiences and repeated practice (Jadhav, 2024). With AI tools like ChatGPT, instructors can create scaffolded worksheets that break down challenging concepts, enabling students to grasp foundational knowledge before moving on to more complex applications. Additionally, using AI to create multiple versions of assessments, as outlined in the Specs Grading approach, supports mastery learning by allowing students repeated attempts on varied questions that reinforce key concepts (Author, in press).

This study builds upon previously published findings by further examining AI-generated scaffolded worksheets, with a particular focus on their impact on faculty workload and administrative efficiency (Author, 2024). While the original study primarily investigated student quiz score improvements, the present research expands the discussion to explore AI integration in higher education from an instructor's perspective. The dataset used in this analysis has been repurposed with permission to extend the scope of inquiry beyond student outcomes.

Using a mixed-methods approach, this study combines quantitative analysis of student performance with qualitative feedback to assess the effectiveness of ChatGPT in achieving instructional and administrative efficiency. Specifically, the study aims to explore the following research questions: (1) How does ChatGPT improve time efficiency in creating personalized study materials and assessments? (2) What impact does ChatGPT have on student engagement and learning outcomes? (3) How

effective is ChatGPT in reducing faculty workload through streamlined administrative support?

This paper presents a case study on the integration of ChatGPT in a General Chemistry course at a regional campus, focusing on four primary areas: study materials for students, course preparation, Specs Grading, and administrative support. By sharing specific prompts and examples, this study illustrates the practical benefits of ChatGPT in creating tailored study materials, automating multi-version quizzes to meet Specs Grading requirements, and assisting with administrative tasks like drafting recommendation letters and summarizing meetings. These applications of ChatGPT not only aim to enhance student engagement and mastery of complex topics, as demonstrated by increased quiz scores and positive feedback ratings, but also offer faculty a valuable resource for managing instructional and administrative workloads efficiently.

While this study demonstrates a measurable improvement in student quiz scores, it is important to recognize that multiple factors contribute to student success. Because all students in the AI-integrated semesters used these worksheets in-class under instructor supervision, self-selection bias was minimized. However, further research using controlled experimental conditions is needed to fully isolate the impact of AI-generated materials on learning outcomes.

Method

1. Study Design

This study was conducted over three consecutive semesters in a General Chemistry I course at a regional campus. The course was taught by the same instructor each semester, using an identical syllabus, grading structure, and assessment design to maintain consistency in instructional delivery. Course topics, lecture slides, and laboratory activities remained unchanged across all semesters to minimize variations in instructional content. The student population included both traditional and non-traditional learners, with an average class size of approximately 40 students per semester. All students enrolled in the course were required to have completed the same chemistry and math prerequisites. While there was no direct control over students' individual academic backgrounds beyond prerequisite coursework, overall student demographics, including age, prior

chemistry exposure, and GPA distribution, remained relatively stable across the three semesters.

To investigate how ChatGPT improves time efficiency in creating personalized study materials and assessments, faculty time spent on course preparation was measured before and after implementing AI-generated resources. The study tracked the time required to develop scaffolded worksheets, multi-version assessments, and study guides using ChatGPT, compared to manually developed versions from previous semesters. Time savings were documented through instructor-reported logs and measured in minutes per task, allowing for a quantitative comparison of AI-assisted versus traditional preparation methods.

The impact of ChatGPT on student engagement and learning outcomes was assessed using two primary data sources. First, Likert-scale surveys were administered at the end of each semester to evaluate student perceptions of AI-generated materials in terms of content clarity, engagement, usefulness, and overall satisfaction. The survey was conducted during a scheduled class session to ensure broad participation from enrolled students. While participation was voluntary, all students present on the survey day were encouraged to respond, resulting in a response rate of approximately 95%. No incentives were provided, and responses were collected anonymously to minimize bias. Since students completed the survey in class, the results reflect a broad representation of those enrolled rather than self-selected participants. However, students who were absent on the survey day did not participate, introducing a potential source of nonresponse bias.

Additionally, changes in student performance were analyzed by comparing quiz scores across semesters. A paired t-test was conducted to determine whether the differences in student quiz scores were statistically significant, providing a quantitative measure of learning gains. Since quizzes directly assessed AI-generated worksheet content, they were selected as the primary metric for evaluating learning gains. Final grades were not used as a performance measure because they incorporate multiple factors beyond quizzes, such as homework, attendance, and participation, which could introduce uncontrolled variability.

The effectiveness of ChatGPT in reducing faculty workload through streamlined administrative support was examined by analyzing faculty self-reported time logs. This included tracking reductions in time spent on routine administrative tasks such as drafting recommendation letters,

summarizing departmental meetings, and creating study materials. Time savings from these tasks were compared to previous semesters, and qualitative faculty feedback was collected to assess perceptions of AI's role in improving administrative efficiency.

To ensure fairness in performance comparisons, all assessments, including quizzes, exams, and laboratory work, remained identical each semester. Additionally, all quizzes and exams were conducted in person, preventing students from using external AI assistance during assessments. While structured classroom use of AI-generated worksheets minimized self-selection bias, students were not pre-selected based on academic ability, prior performance, or interest in AI. All students in AI-integrated semesters were required to use the worksheets under instructor supervision, ensuring uniform exposure. However, variations in individual study habits, external tutoring, and previous chemistry experience may have influenced learning outcomes.

2. Effectiveness of AI in Classroom Instruction

To investigate ChatGPT's effectiveness in classroom instruction, AI-generated scaffolded worksheets and study guides were used to support student learning. These resources were designed to improve student comprehension of complex chemistry topics by gradually building knowledge from foundational to advanced concepts. ChatGPT assists in creating these scaffolded materials by breaking down topics into manageable steps, a method shown to enhance student learning through gradual mastery (Wood et al., 1976; Kinchin, 2006). This approach aligns with Student Learning Objectives (SLOs) and facilitates incremental learning, especially in subjects requiring foundational knowledge like chemistry.

Sample Prompts for Scaffolded Worksheets:

- "Create a scaffolded worksheet on stoichiometry, beginning with basic mole calculations and progressing to limiting reactants."
- "Generate a step-by-step guide on balancing redox reactions, with explanatory notes at each step."

Using these prompts, ChatGPT generates worksheets that guide students from basic to more advanced concepts. This method encourages gradual mastery and supports independent learning. Prior research

indicates that AI-driven tools can effectively personalize instruction, enhancing student engagement and learning (Murtaza et al., 2022; Holmes et al., 2019).

To measure student engagement and perceptions of AI-generated materials, a post-semester Likert-scale survey was administered. The survey contained ten questions evaluating content clarity, engagement, usefulness, and overall satisfaction, with responses ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Additionally, student quiz scores were compared across semesters to assess learning improvements. A paired t-test was conducted to determine whether the differences in quiz scores were statistically significant, allowing for an objective evaluation of the impact of AI-generated resources on student learning outcomes. Table 1 provides an example of the scaffolded structure for a stoichiometry worksheet generated by ChatGPT. For full examples, see Appendix A and B.

Table 1: Stepwise Approach in ChatGPT-Generated Stoichiometry Worksheet

Step	Topic	Example Question/Activity
1	Mole Concept Basics	Calculate moles of NaCl given 5 grams.
2	Stoichiometric Ratios	Given a balanced equation, identify the limiting reactant.
3	Applied Problem on Limiting Reactants	Calculate the yield in grams based on the limiting reactant.

Real-Life Chemistry Examples

In addition to scaffolded worksheets and study guides, ChatGPT was employed to create real-life examples of chemistry concepts, allowing students to see the relevance of these topics beyond the classroom. These examples were designed to make abstract concepts more relatable by connecting them to familiar, everyday phenomena, such as the chemistry of batteries, cleaning agents, and combustion. Context-based learning has been shown to enhance student engagement and comprehension in STEM fields (Clark & Mayer, 2016; Nye, 2015).

Sample Prompts for Real-Life Chemistry Examples: (For full examples, see Appendix C)

- "Provide examples of oxidation-reduction reactions in everyday life, with explanations of how and where they occur."
- "Generate real-life scenarios where acid-base reactions are essential, such as in cleaning products or food chemistry."
- "Explain the chemistry behind combustion in engines and how it converts fuel into energy."

These examples were designed to make chemistry more relatable by connecting theoretical concepts to real-world applications, supporting student engagement and retention.

3. Impact of AI-Generated Feedback on Student Learning

To evaluate ChatGPT's role in providing feedback and enhancing student learning, the AI tool was used to generate multiple versions of Quests (a combination of quiz and test) aligned with the Specifications Grading (Specs Grading) approach. Specs Grading requires students to demonstrate mastery of specific learning outcomes. By providing multiple opportunities of the unique assessment versions, ChatGPT supports iterative practice, reinforcing students' understanding and retention of key concepts. Adaptive assessments have been shown to support mastery learning by allowing students to repeatedly engage with varied but conceptually aligned content (Clark & Mayer, 2016; Nye, 2015). ChatGPT aids this process by creating multiple versions of assessments that address similar learning outcomes but vary in their content, thus promoting mastery without redundancy.

Prompts for Creating Multi-Version Quests:

- "Create three versions of a quest question on molar mass calculation, each with different compounds and masses."
- "Generate unique assessment versions on limiting reactants for students retaking the quest."

Table 2 provides examples of multi-version Quest questions created by ChatGPT, demonstrating how different versions assess the same skillset while offering diverse problem sets. This flexibility supports students'

engagement and aligns with the mastery-focused approach of Specs Grading.

Table 2: Examples of Multi-Version Quest Questions for Specs Grading using ChatGPT

Version	Question Example
1	Calculate the theoretical yield of H_2 when 10g of Zn reacts with HCl.
2	Determine the yield of O_2 produced from 12g of $KClO_3$.
3	Find the grams of CO_2 produced from 8g of C reacting with O_2 .

By using ChatGPT to automate the creation of these varied assessments, the average preparation time was reduced by approximately 25%, from 40 minutes per assessment to about 30 minutes. Further details on time savings are presented in the Results section.

4. Impact of AI on Instructor Efficiency and Workload

The third research question examines how ChatGPT affects instructor efficiency by reducing the time spent on both course preparation and routine administrative tasks. Faculty members at regional campuses often balance teaching responsibilities with administrative duties, making time management essential. ChatGPT assists by automating repetitive tasks, allowing faculty to reallocate time to direct student engagement and course development (West, 2018; Guan et al., 2020).

In addition to instructional support, ChatGPT helps streamline routine tasks such as drafting letters of recommendation, summarizing meeting notes, and organizing student performance data.

Sample Prompt for Administrative Tasks:

- “Draft a one-page letter of recommendation for a student who was in the top 5% in my chemistry course and demonstrated excellent lab skills.”

To evaluate time savings, the duration of each task was measured before and after using ChatGPT. Faculty workload reductions were quantified by tracking the time spent on three key tasks before and after ChatGPT integration: developing study materials, grading and assessment preparation, and administrative tasks such as writing recommendation

letters and summarizing meeting notes. Time logs were maintained over three semesters, and an average time reduction percentage was calculated. Additionally, qualitative insights on perceived efficiency improvements were gathered through informal reflections on teaching and administrative workload.

Results and Discussion

This study evaluated the impact of ChatGPT on enhancing instructional quality and administrative efficiency in a General Chemistry course. The findings are organized according to the three primary research areas: the effectiveness of AI-generated materials in classroom instruction, the impact of AI on student learning and engagement, and the role of AI in improving instructor workload efficiency. The integration of ChatGPT in classroom instruction aimed to improve students' understanding of complex chemistry topics through AI-generated scaffolded worksheets and personalized study guides. These AI-generated materials align with scaffolded learning theories, which emphasize gradual mastery of complex topics by breaking them down into manageable steps (Wood et al., 1976; Kinchin, 2006).

Effect of AI-Generated Worksheets on Student Performance

Results indicate a statistically significant improvement in student performance following the integration of AI-generated scaffolded worksheets. A paired t-test was conducted to compare quiz scores across semesters. The analysis showed a significant increase in quiz scores from Fall 2022 ($M = 70.3$, $SD = 5.4$) to Fall 2023 ($M = 75.8$, $SD = 6.1$), with $t(39) = 4.75$, $p < 0.001$. The observed 3.5-point increase corresponds to an improvement of approximately 5% in quiz performance, which is statistically significant and practically meaningful in the context of student learning. As shown in Table 3, the progression of quiz scores across semesters reflects the impact of AI-generated worksheets on student comprehension. Given that quizzes are a direct measure of conceptual understanding, this increase suggests that students using AI-generated materials demonstrated improved mastery of the covered topics.

Table 3: Average Quiz Scores Across Semesters

Semester	Average Quiz Score
Fall 2022 (Baseline, no AI)	70.3
Spring 2023 (Pilot, AI materials)	73.5
Fall 2023 (Full AI integration)	75.8

A paired t-test confirmed that the observed increase in quiz scores was statistically significant ($p < 0.001$), indicating that the improvement was unlikely due to random variation. However, while these results strongly suggest that AI-generated scaffolded worksheets contributed to increased comprehension, other factors such as individual student motivation, external study habits, and prior knowledge could also play a role. Since all students in the AI-integrated semesters used these worksheets in a structured classroom setting, the likelihood of self-selection bias was minimized. Future research using controlled experimental conditions or randomized student groups may further isolate the direct causal impact of AI-generated materials. Additionally, students were explicitly informed that ChatGPT-generated worksheets may contain inaccuracies and were encouraged to verify all calculations and explanations. Classroom discussions were conducted to review and validate AI-generated responses before students applied them to assessments.

Student Perceptions of AI-Generated Materials

To assess ChatGPT's role in enhancing student learning, a Likert-scale survey was administered at the end of the Fall 2023 semester. The survey consisted of ten questions evaluating students' perceptions of AI-generated materials in terms of content clarity, engagement, usefulness, and overall satisfaction. This survey was previously published in Author (2024), where the results were presented as a bar graph. In this study, the same data is represented in Table 4 in tabular format for clarity and direct comparison within the current analysis.

The survey was conducted in class, and 38 out of 40 students participated, resulting in a 95% response rate. Since participation was not mandatory, there is a potential response bias, as students who found the AI-generated worksheets beneficial may have been more likely to provide feedback. Future studies should explore mandatory feedback collection or randomized survey distribution to obtain a more representative sample of student experiences.

As shown in Table 4, students rated the AI-generated materials positively, with average scores of 4.4 for content clarity, 4.3 for engagement, and 4.5 for overall satisfaction on a 5-point scale. While Table 4 highlights three representative survey questions, the full survey results are available in Appendix D. These findings suggest that AI-generated worksheets enhanced student engagement and comprehension; however, future research should implement structured, randomized feedback collection to minimize potential self-selection bias in survey responses.

Table 4: Student Feedback on AI-Generated Materials (Likert Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

Survey Category	Average Score
Content Clarity	4.4
Engagement	4.3
Overall Satisfaction	4.5

The positive reception indicates that AI-generated materials effectively enhance student engagement and clarity, which is particularly beneficial in mastering complex chemistry topics. However, since the survey was conducted in class, participation was voluntary, meaning that students who found the AI worksheets beneficial may have been more likely to provide feedback. Future studies should incorporate mandatory feedback collection or randomized survey distribution to reduce potential response bias and obtain a more representative understanding of student perceptions.

Additionally, some students noted the need for more tailored support in advanced topics, suggesting that further refinement of ChatGPT-generated prompts could improve effectiveness for complex problem-solving. This highlights the importance of faculty oversight in AI-generated content creation, ensuring that materials remain pedagogically sound, conceptually accurate, and aligned with course objectives.

AI Use and Ethical Considerations

ChatGPT was used in refining this manuscript by improving structure and clarity. However, all AI-generated content was manually reviewed and edited to ensure accuracy and coherence. While AI-generated materials provided valuable instructional support, they were not assumed to be error-free and could contain inaccuracies. To address this, students

were explicitly informed that ChatGPT-generated worksheets were supplementary resources, and all calculations should be verified. Classroom discussions were held to review and correct any conceptual errors before students applied the materials to assessments.

To promote responsible AI use, students were guided in recitation sessions on how to effectively use structured AI-generated prompts. These sessions helped students break down complex chemistry problems using scaffolded AI explanations while maintaining active engagement in problem-solving. Faculty oversight ensured that AI was used as a learning aid rather than a substitute for critical thinking.

To maintain academic integrity, all assessments, including quizzes and exams, were conducted in person, preventing students from relying on AI-generated answers. This approach ensured that students demonstrated independent knowledge while reinforcing problem-solving skills.

Faculty AI Use in Writing and Research Productivity

In addition to instructional applications, AI tools like ChatGPT have the potential to support faculty research and writing processes. In this study, ChatGPT was used to refine sections of the manuscript, particularly for structuring content and enhancing clarity. However, all AI-generated text was critically reviewed, manually revised, and fact-checked to ensure accuracy and coherence. The use of AI-assisted writing tools aligns with best practices in academic writing, where researchers employ grammar checkers, reference managers, and AI-powered summarization tools to streamline the writing process while maintaining intellectual rigor and authorship integrity. Beyond instructional applications, AI can play a valuable role in faculty research productivity, particularly in idea generation, literature review synthesis, and draft refinement. For instance, ChatGPT was used to generate concise summaries of key literature sources, allowing faculty to streamline the synthesis of research on AI-assisted learning methodologies. Additionally, AI-assisted tools helped refine research questions and identify emerging themes in the field, contributing to more structured and focused academic writing.

However, AI-generated content must always be critically reviewed, revised, and properly credited to ensure accuracy and uphold academic integrity. Future research should explore ethical best practices for AI-assisted research writing, including clear attribution protocols and validation methods. Further studies should also examine AI's impact on

faculty workload in academic publishing, particularly in reducing time spent on literature reviews, manuscript drafting, and editing while maintaining scholarly rigor.

Study Implications

Structured AI Use in Course Instruction

Structured AI use in lecture and recitation sessions played a critical role in ensuring that students engaged thoughtfully with ChatGPT-generated content rather than relying on it passively. By incorporating guided AI prompts and faculty-supervised interactions, students were encouraged to develop independent problem-solving strategies. This structured approach positioned AI as a scaffolded learning tool rather than a replacement for traditional instruction.

Future research should explore best practices for integrating AI into STEM education, particularly in balancing AI-driven support with active student engagement. Additionally, further studies should examine AI's influence on long-term knowledge retention and its impact on final course grades through controlled studies. Establishing a standardized framework for AI-assisted learning materials could promote instructional consistency while maintaining academic rigor.

Faculty AI Use Transparency

Faculty using AI-generated instructional materials should disclose their use to students, much like publisher-provided resources such as test banks and slide decks are credited. Transparency ensures ethical implementation while encouraging students to critically engage with AI-generated content. This practice aligns with broader academic integrity principles and helps students understand AI's evolving role in education.

AI Limitations and Accuracy Concerns

While AI-generated materials can enhance student learning, they may produce errors or inaccuracies. Faculty and students must critically evaluate AI-generated content to ensure accuracy. Instructors in this study reviewed worksheet content in class to confirm conceptual accuracy before students applied the material to assessments. Students were also reminded to verify ChatGPT-generated calculations against verified sources such as textbooks or instructor-provided materials. To further ensure content reliability, students engaged in structured discussions where AI-generated

explanations were compared with traditional instructional materials, allowing them to identify and correct potential inaccuracies collaboratively.

Future research should explore structured validation methods to minimize AI-generated errors and establish best practices for integrating AI-assisted materials into courses. This could include developing systematic review processes for AI-generated content, incorporating instructor-led verification protocols, and designing student training on effective AI evaluation strategies. Investigating how AI-generated materials impact long-term retention and academic performance through controlled studies will also be essential for understanding their role in higher education.

Student Use of AI and Academic Integrity

A key concern is whether students use ChatGPT to generate quiz answers instead of engaging with the learning process. While students were encouraged to critically evaluate AI-generated responses, additional research is needed to assess how AI affects independent problem-solving skills. Faculty should implement strategies that promote constructive AI use while maintaining academic integrity. These strategies could include structured AI-assisted exercises, guided reflections on AI-generated content, and assessments that require students to explain their reasoning rather than simply providing an AI-generated answer.

Instructor Efficiency and Administrative Benefits

ChatGPT significantly improved instructor efficiency by reducing the time needed for both course preparation and routine administrative tasks. Generating multiple versions of Quizzes manually took approximately 40 minutes per version, while ChatGPT reduced this time to around 30 minutes, resulting in a 25% time savings. The Specs Grading system benefited from this efficiency gain, allowing students to retake assessments with unique versions and support mastery learning.

This efficiency is particularly evident in assessment preparation, where AI-assisted workflows significantly reduced the time required to generate multiple versions of Quizzes. As shown in Table 5, AI reduced quiz development time by an average of 28 minutes across assessments, allowing instructors to allocate more time to student-centered activities.

Table 5: Time Savings in Assessment Preparation with ChatGPT Assistance

Task	Manual Creation Time	AI-Assisted Time	Time Saved
Stoichiometry Quiz	45 minutes	30 minutes	15 minutes
Limiting Reactant Quiz	43 minutes	30 minutes	13 minutes
Total Across Assessments	88 minutes	60 minutes	28 minutes

In addition to supporting instruction, ChatGPT significantly improved efficiency in routine administrative tasks, such as drafting recommendation letters, summarizing meeting notes, and organizing student performance data. Before using ChatGPT, drafting a recommendation letter took approximately 30 minutes; with ChatGPT, the time was reduced to about 10 minutes, saving 20 minutes per letter. As summarized in Table 6, faculty reported an overall 60% reduction in time spent on these administrative tasks, highlighting AI's role in improving workflow efficiency.

Table 6: Time Savings Achieved Through AI-Assisted Administrative Tasks

Task	Pre-AI Time	AI-Assisted Time	Time Saved per Task
Drafting Recommendation Letter	30 minutes	10 minutes	20 minutes
Summarizing Meeting Notes	45 minutes	15 minutes	30 minutes
Organizing Student Data	25 minutes	10 minutes	15 minutes
Total Savings Across Tasks	-	-	65 minutes

The 60% reduction in time for these administrative tasks has allowed faculty to invest more time in direct student engagement and course development, aligning with studies that show AI's effectiveness in improving operational efficiency (West, 2018; Guan, Mou, & Jiang, 2020). Although ChatGPT streamlines administrative tasks, it is essential to review AI-generated documents to maintain professionalism and relevance. Faculty should check all outputs for accuracy and coherence before finalizing. These

findings suggest that ChatGPT is a valuable tool for regional campus faculty, supporting both instructional and administrative efficiency. By automating repetitive tasks, ChatGPT enables instructors to focus on higher-impact activities, such as interactive teaching and personalized feedback, which are essential for enhancing student learning outcomes.

Limitations

While ChatGPT offers advantages in instructional efficiency and administrative support, its application has limitations. AI-generated content requires continuous validation, as probabilistic models may introduce miscalculations or conceptual errors. Students were explicitly informed to use AI-generated worksheets as supplementary resources and to verify all calculations against textbooks or instructor-provided materials. Instructors also conducted in-class discussions to identify and correct any AI-generated inaccuracies before assessments.

Faculty using AI-generated instructional materials disclosed this use to students, ensuring transparency similar to publisher-provided resources (e.g., test banks, slide decks). This helped students critically evaluate AI-generated content rather than relying on it uncritically. Additionally, AI-generated responses were not permitted for graded assignments, and quizzes required students to show problem-solving steps to uphold academic integrity.

This study was conducted in a General Chemistry I course, and findings may not fully generalize to other disciplines where AI-generated scaffolding may function differently. While all students had the same chemistry and math prerequisites, variations in prior exposure, independent study habits, and access to external academic resources may have influenced their performance. Future research with controlled experimental conditions and randomized student groups could provide a clearer understanding of AI's direct impact on learning outcomes.

Although quiz score improvements were statistically significant ($p < 0.001$), it remains unclear whether these gains translate to broader academic success, such as final exam performance or course grades. Since quizzes primarily assess conceptual understanding, future studies should explore AI's impact on cumulative assessments and long-term retention. Survey responses were collected voluntarily, with 95 percent of students (38 out of 40) participating. While this provides useful insights, response bias may exist, as students who found the AI worksheets beneficial may have

been more likely to provide feedback. Future studies should consider mandatory feedback collection or randomized survey distribution to ensure a more representative assessment of student perspectives.

While ChatGPT-generated materials supported structured learning, faculty emphasized the importance of critical evaluation to prevent over-reliance on AI-generated responses. As AI continues to evolve, further research should explore structured validation methods to minimize AI-generated errors and improve instructional reliability.

In summary, ChatGPT enhances instructional quality and faculty efficiency by providing structured, scaffolded resources and automating routine tasks. However, careful faculty oversight, academic integrity policies, and structured implementation are essential to ensure accuracy and pedagogical effectiveness.

Conclusion

Integrating ChatGPT into teaching and administrative tasks has demonstrated benefits for both faculty efficiency and student learning outcomes on a regional campus. AI-generated scaffolded worksheets, personalized study guides, and multi-version assessments have enhanced student comprehension of complex chemistry topics, increased engagement, and supported mastery-oriented learning through the Specifications Grading framework. Research has shown that scaffolded learning fosters incremental mastery, and AI's ability to generate structured learning materials aligns with this pedagogical approach. The findings indicate that these resources contribute to improved student performance, as reflected in increased quiz scores and positive student feedback on content clarity and overall satisfaction.

Beyond instructional benefits, ChatGPT has streamlined routine administrative tasks such as drafting recommendation letters and summarizing meeting notes, saving faculty significant time. The study results show that up to 65 minutes per day can be redirected toward direct student engagement and course development, ultimately enhancing instructional quality. The automated creation of multi-version assessments also provides students with additional practice opportunities, reinforcing understanding without content duplication—a feature particularly valuable in mastery-based grading systems.

Despite these advantages, AI-generated content requires careful oversight to ensure accuracy, pedagogical soundness, and instructional

relevance. Faculty must critically evaluate AI-generated outputs to maintain the integrity of educational materials and administrative documents. This study implemented structured discussions where students compared AI-generated explanations with traditional materials, encouraging them to identify inaccuracies and refine their understanding. Such strategies ensure that AI is used as a supportive tool rather than a substitute for active learning.

The findings suggest that AI tools like ChatGPT can play a transformative role in education, particularly in regional campus settings where faculty often balance high teaching loads with administrative responsibilities. AI-driven solutions support the broader goals of accessible, high-quality education by providing scalable, efficient, and personalized learning resources. Future research should explore structured validation protocols to minimize AI-generated errors, examine AI's impact on student retention and long-term knowledge retention, and investigate best practices for faculty training in AI-assisted teaching. Establishing clear guidelines for responsible AI integration will be essential to maximizing its benefits while maintaining academic rigor.

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Appendix A: AI-Generated Resources for Chemistry Instruction

The following tables summarize the types of instructional and assessment materials generated using ChatGPT to support General Chemistry students. These resources were designed to align with specific Student Learning Objectives (SLOs) and to facilitate mastery-focused learning through scaffolded worksheets, personalized study guides, real-world applications, and multi-version assessments for Specs Grading. Each table provides sample prompts, example questions, and descriptions of how these materials are structured to cater to diverse learning needs. By using AI, faculty can efficiently create adaptive learning materials that support both foundational understanding and complex problem-solving skills.

Table 7: Summary of AI-Generated Resources and Examples in Chemistry Instruction

Resource Type	Purpose	Sample Prompt/Description	Example Use Case
Scaffolded Worksheets	Support incremental mastery of complex concepts through structured steps	"Create a scaffolded worksheet on stoichiometry, starting with basic mole calculations and progressing to limiting reactants."	Topic: Stoichiometry Steps: 1) Mole Concept Basics – Calculate moles of NaCl for 5g 2) Stoichiometric Ratios – Identify limiting reactant 3) Applied Problems – Calculate yield based on limiting reactant
Study Guides	Reinforce key concepts and provide targeted practice for self-study	"Develop a study guide for acid-base reactions with key concepts and practice problems."	Topic: Acid-Base Reactions Content: Overview, key concepts, sample problems with solutions
Real-Life Chemistry Examples	Connect theory to real-world applications,	"Provide examples of oxidation-reduction reactions in everyday	Examples: Rusting, combustion, photosynthesis, with

	enhancing engagement	life, with explanations."	explanations of each reaction
Customized Worksheets	Adapt materials to different levels of prior knowledge	"Generate a worksheet that adjusts stoichiometry questions for various student skill levels."	Customization: Vary question complexity based on student proficiency
Multi-Version Quests for Specs Grading	Facilitate mastery-focused retakes by offering varied versions of assessments	"Create three versions of a quest question on molar mass calculation, each with different compounds and masses."	Quest Versions: 1) Yield of H ₂ from Zn + HCl 2) O ₂ yield from KClO ₃ 3) CO ₂ yield from C + O ₂
Practice Problems	Provide targeted problem-solving practice with step-by-step solutions	"Create five practice problems on acid-base titration with step-by-step solutions."	Example Problems: Titration calculations, identifying endpoints, acid-base balance

Appendix B: Sample Response for Scaffolded Worksheet on Stoichiometry

This scaffolded worksheet progresses from simple to complex concepts, reinforcing each step with examples and practice. This approach allows students to build a solid foundation in stoichiometry, setting them up for success in more advanced topics.

Prompt: "Create a scaffolded worksheet on stoichiometry, beginning with basic mole calculations and progressing to limiting reactants."

ChatGPT-Generated Worksheet

Topic: Stoichiometry – From Moles to Limiting Reactants

Objective: This worksheet guides students through the fundamental steps of stoichiometry, starting with mole calculations and advancing to limiting reactants. Each section includes examples and practice problems to reinforce understanding.

Step 1: Mole Calculations

1. **Introduction:** Understanding moles is crucial in chemistry as it allows us to relate masses of substances to the number of atoms or molecules.
2. **Example Question:** Calculate the number of moles in 10 grams of NaCl.

$$\text{Solution: Molar mass of NaCl} = 58.44 \frac{\text{g}}{\text{mol}}$$

$$\text{Moles of NaCl} = 10 \text{ g NaCl} \times \frac{1 \text{ mol of NaCl}}{58.44 \text{ g NaCl}} = 0.171 \text{ mol NaCl}$$

3. **Practice Problem:** Calculate the number of moles in 25 grams of H₂O.

Step 2: Stoichiometric Ratios

1. **Introduction:** In a chemical reaction, substances react in specific ratios. Stoichiometry helps us calculate how much of each substance is needed or produced.
2. **Example Question:** In the reaction $2 \text{H}_2 + \text{O}_2 \rightarrow 2\text{H}_2\text{O}$, how many moles of O₂ are required to react completely with 4 moles of H₂

Solution: According to the balanced equation, 2 mol of H₂ reacts with 1 mol of O₂

$$\text{Moles of O}_2 = 4 \text{ mol H}_2 \times \frac{1 \text{ mol of O}_2}{2 \text{ mol of H}_2} = 2 \text{ mol of O}_2$$

3. **Practice Problem:** In the reaction $3 \text{H}_2 + \text{N}_2 \rightarrow 2 \text{NH}_3$ how many moles of NH₃ are produced when 6 moles of H₂ react?

Step 3: Limiting Reactants

1. **Introduction:** When reactants are not in perfect stoichiometric ratios, one will run out first and limit the reaction. This is called the limiting reactant.
2. **Example Question:** In the reaction $2 \text{H}_2 + \text{O}_2 \rightarrow 2\text{H}_2\text{O}$, if you have 3 moles of H₂ and 2 moles of O₂, which is the limiting reactant?

Solution: According to the equation, 2 moles of H₂ requires 1 mole of O₂

$$\text{Moles of O}_2 = 3 \text{ mol H}_2 \times \frac{1 \text{ mol of O}_2}{2 \text{ mol of H}_2} = 1.5 \text{ mol of O}_2$$

Since you have 2 moles of O₂, H₂ is the limiting reactant.

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3. **Practice Problem:** For the reaction $2Al + 3Cl_2 \rightarrow 2AlCl_3$, if you have 5 moles of Al and 5 moles of Cl_2 , which reactant is limiting?

Appendix C: Real-Life Chemistry Examples

To make complex chemistry concepts more relatable and engaging, ChatGPT was used to generate real-life applications of chemistry principles. These examples help students see the relevance of their studies beyond the classroom, enhancing their understanding and interest in the subject.

Sample Prompts for Real-Life Chemistry Examples

- Oxidation-Reduction Reactions: "Provide examples of oxidation-reduction reactions in everyday life, with explanations of how and where they occur."
- Acid-Base Reactions: "Generate real-life scenarios where acid-base reactions are essential, such as in cleaning products or food chemistry."
- Combustion and Energy: "Explain the chemistry behind combustion in engines and how it converts fuel into energy."

Example Responses from ChatGPT

1. Oxidation-Reduction in Batteries: "Batteries rely on oxidation-reduction reactions to generate electricity. In a zinc-carbon battery, zinc undergoes oxidation while manganese dioxide is reduced, creating a flow of electrons that powers electronic devices."
2. Acid-Base in Cleaning Products: "Many cleaning agents contain bases, like sodium hydroxide, which reacts with oils and greases to form water-soluble substances, making cleaning more effective. Vinegar (acetic acid) is an acid commonly used to dissolve mineral deposits due to its acidic properties."
3. Combustion in Automobiles: "In car engines, gasoline combustion produces energy. The carbon and hydrogen in gasoline react with oxygen, releasing energy in the form of heat and producing carbon dioxide and water as by-products."

Appendix D: Full List of Likert Survey Questions

The following survey questions were previously published in Author (2024) and are provided here for reference. The average scores reflect student responses on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

1. Clarity of content (M = 4.4)
2. Usefulness in learning (M = 4.3)
3. Preparedness for assignments (M = 4.2)
4. Engagement level (M = 4.3)
5. Ease of application (M = 4.1)
6. Interaction with peers (M = 3.9)
7. Independence in learning (M = 4.0)
8. Preparedness for assessments (M = 4.2)
9. Preference for scaffolded worksheets (M = 4.5)
10. Overall experience (M = 4.5)

Taking a leaf from experts on effective instructional approaches related to the teaching of optimization problems in calculus

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This study used a qualitative questionnaire to elicit experts' views regarding effective instructional approaches related to the teaching of optimization problems in first-semester calculus. A thematic analysis was conducted on responses from 11 instructors who completed the questionnaire. It revealed that all the instructors considered the construction and use of diagrams, providing students with a set of steps to follow, and creating ample individual and group opportunities (during course lectures and outside the classroom) to be helpful in supporting students' learning about these types of problems. The experts further identified several technologies, including Desmos, GeoGebra, and WebAssign visuals, they consider to be helpful in supporting students' learning about optimization problems. Additionally, the experts provided helpful insights regarding calculus textbooks' strengths and weaknesses in their presentation of optimization problems. Implications for different stakeholders, including calculus instructors and textbook selection committees in mathematics departments, are discussed.

1. Introduction

Optimization problems not only form an integral part of first-semester calculus, commonly referred to as Calculus I in the United States, but they are also a type of problems that are well known to be particularly challenging for students to solve (cf. LaRue & Infante, 2015). In fact, there is a substantial and growing body of research that has reported on students' difficulties when working with optimization problems (cf. Borgen & Manu, 2002; Brijlall & Ndlovu, 2013; Heid, 1988; Klymchuk et al., 2010; Maharaj, 2013; Mkhathswa, 2016, 2019; Swanagan, 2012; Ubuz & Ersoy, 1997; Villegas et al., 2009; White & Mitchelmore, 1996). Thus, the current study aims to create a resource of teaching strategies. These strategies are designed to address previously reported students' difficulties when working optimization problems. To accomplish this, the current study examined veteran calculus instructors' (hereafter, experts) views on effective

instructional approaches related to the teaching of optimization problems in Calculus I.

Calculus I is typically taught by instructors with a wide spectrum of teaching experience, including graduate students who often serve as teaching assistants, early career and tenure-track (probationary) professors, and late career and tenured (permanent) professors in the United States. It is my hope that the list of effective teaching approaches presented in this study will be especially helpful for any instructor with a limited or no calculus teaching experience at all, regardless of the stage of their teaching career, namely early, middle, or late career stage, respectively. After all, evidence from research shows that instructors tend to look to research for help on how to best teach certain concepts/topics in their disciplines. (cf. Drill et al., 2013).

Advances in technology have led to a rise in the invention and usage of various educational technologies in the teaching of many undergraduate mathematics courses in the United States, including Calculus I. Furthermore, a number of studies have reported on instructors' propensity to closely follow the presentation of content in mathematics textbooks during course lectures (cf. Mkhathswa, 2016; Reys et al., 2004). Thus, in addition to examining experts' views regarding best practices in the teaching of optimization problems, the present study investigated experts' perceptions regarding the role of technology and calculus textbooks in the teaching of optimization problems in Calculus I. In essence, the present study seeks to address the following research questions:

1. What do veteran calculus instructors consider to be effective instructional strategies in the teaching of optimization problems in Calculus I?
2. What teaching technologies do experienced calculus instructors use in their teaching of optimization problems in Calculus I?
3. What do calculus instructors identify as weaknesses and strengths in the presentation of optimization problems in Calculus I textbooks?

2. Related Literature

2.1 Students' difficulties when working with optimization problems

While the main focus of the present study is on effective instructional approaches related to the teaching of optimization problems in

Calculus I, it is worthwhile to review existing literature on students' difficulties when working with optimization problems for comparison. Specifically, this will help determine the extent, if possible, to which the teaching strategies presented in this study could potentially address (or fail to address) students' difficulties with optimization problems previously reported in the research literature.

A common theme that emerges from research that has examined students' thinking about optimization problems in Calculus I is that formulating the objective function i.e., the function whose minimum/maximum value is to be found is generally problematic for students (cf. Klymchuk et al., 2010; Mkhathshwa, 2019; Swanagan, 2012; Villegas et al., 2009; White & Mitchelmore, 1996). In fact, LaRue and Infante (2015) observed that this is problematic even when students are tasked with solving routine optimization problems where constructing the objective function is simple, and observation also made by Klymchuk et al. (2010). Another common finding is that students often struggle with finding critical numbers or extreme values of the objective function, even after successfully formulating the function (cf. Brijlall & Ndlovu, 2013; Dominguez, 2010; Mkhathshwa, 2019; Swanagan, 2012). As a matter of fact, findings by Swanagan (2010) indicate that sometimes students rely on guesswork to determine an objective function's critical numbers or extreme values. Lastly, several researchers have found that verifying/justifying extrema using formal methods such as the first or second derivative test is particularly challenging for many students when working with optimization problems in Calculus I (cf. Borgen & Manu, 2002; Mkhathshwa, 2019). Part of this challenge stems from not being able to recall these formal methods or applying them incorrectly.

2.2 The role of technology in the teaching of optimization problems

One of the items in the questionnaire used in this study specifically asked experts about the technologies they use and how they use these technologies in their teaching of optimization problems. Consequently, this section provides a survey of literature on the use of technology in the teaching and learning of optimization problems. To date, only two studies have reported on the use of technology in the teaching or assessment of students' learning about optimization problems in calculus. Çekmez (2021) reported on a control group whose exposure to optimization problems was limited to a traditional lecture method and an experimental group whose

exposure to optimization problem involved the use of GeoGebra, a dynamic mathematics software. Analysis of students' performance in an optimization problem they were asked to solve revealed that students in the experimental group outperformed their counterparts in the control group. Furthermore, students in the experimental group demonstrated superior understandings of the quantities and relationships among the quantities involved in the optimization problem compared to their counterparts in the control group. Arango et al. (2015) reported on a successful incorporation of GeoGebra in the teaching of optimization problems in calculus. These researchers remarked that the use of GeoGebra complements paper-based methods of solving optimization problems in that it affords students the ability to visualize the critical number(s) and extreme value(s) of the objective function. Additionally, results from Arango et al.'s (2015) study suggest that GeoGebra is a useful tool that could be used by students to, among other things, verify the correctness of their paper-based solutions when working with optimization problems in calculus.

2.3 The role of textbooks in the teaching and learning of mathematics

While the principal aim of the current study is to explore, through the lens of experts' teaching experiences of Calculus I, effective instructional approaches related to optimization problems, it is crucial to examine the role of textbooks in the teaching and learning of mathematics in general. Most importantly, one of the items in the questionnaire used in the present study elicited experts' perceptions regarding strengths and weaknesses in the presentation of optimization problems by calculus textbooks. Although much research has reported on opportunities to learn provided in K-12 mathematics textbooks, and only a few studies have examined similar opportunities provided by undergraduate mathematics textbooks. Until now, only two studies (Mkhatshwa, 2023; Mkhatshwa & Doerr, 2016) have reported on the opportunity to learn about optimization problems provided by undergraduate calculus textbooks in the United States. Findings of these studies indicate that calculus textbooks in the United States are dominated by tasks with a camouflage context, tasks with matching information, and reproduction tasks i.e., low cognitive demand tasks.

A common finding of research that has examined the relationship between opportunities to learn provided by classroom instruction and mathematics textbooks at both the K-12 level and at the university level is that the presentation of content, including optimization problems in

calculus, during courses lectures tend to closely follow the presentation of similar content in mathematics textbooks (cf. Begle, 1973; Mkhathswa, 2016; Reys et al., 2004; Wijaya et al., 2015). In fact, Reys et al. (2004) eloquently argued that "...the choice of textbooks often determines what teachers will teach, how they will teach it, and how their students will learn" (p. 61), a sentiment that has been shared by other scholars (cf. Begle, 1973). Motivated by the importance of textbooks in students' learning about mathematics, the present study seeks to document experts' perspectives regarding opportunities to learn about optimization problems provided by calculus textbooks in the United States.

3. Methods

3.1 The questionnaire: Design and validation

This qualitative study used an eleven-item online Qualtrics questionnaire (please see Appendix A) that was administered in the fall semester of 2022 to examine experts' views on the teaching of optimization problems in calculus I, among other things. The principal objective of the study was to investigate effective ideas and strategies related to the teaching of optimization problems in Calculus I. Other than Questions 1 and 2 in the questionnaire that were included to elicit experts' experiences with teaching Calculus I and the nature (in terms of research productivity) of the academic institutions they were affiliated with at the time of completing the questionnaire, the rest of the questions in the questionnaire were for the most part informed by findings of existing literature on students' thinking about optimization problems at the level of Calculus I.

The goal for designing the questionnaire was six-fold. First, to gain insight on what calculus instructors consider to be easy/challenging for students when working with optimization problems (Items 3 and 4 in the questionnaire). Second, to gain insight on what calculus instructors consider to be effective instructional approaches in the teaching of optimization problems (Item 5 in the questionnaire). Third, to gain insight on calculus instructors' perceptions regarding the role of technology, or other instructional tools, in the teaching of optimization problems (Item 6 and 7 in the questionnaire). Fourth, to gain insight on frequently used real-world contexts, if any, in the teaching of optimization problems (Item 8 in the questionnaire). Fifth, to gain insight on the range (wide or limited) of textbooks used by experts in the teaching of optimization problems (Item 9 in the questionnaire). Sixth, to gain insight on calculus instructors' views

regarding strengths and weaknesses in the presentation of optimization problems in calculus textbooks (Items 10 and 11 in the questionnaire).

Three subject experts were invited to comment on two aspects of validity, namely face validity and content validity, as it relates to the questionnaire used in the current study. I remark that these experts are not among the 11 experts who are participants in the study. They all had sufficient experience teaching and tutoring students taking Calculus I in the United States. In using the term face validity, I am refereeing to the suitability of the questionnaire in addressing the research questions investigated in the study (Martinez, 2017). Furthermore, in using the term content validity, I refer to the questionnaire's ability to capture all aspects related to the teaching and learning of optimization problems in calculus (Martinez, 2017). In their independent evaluations of the questionnaire, the three experts deemed the questionnaire to be valid in terms of the two aspects of validity that were assessed i.e., face validity and content validity.

3.2 Sampling method and participants

Using convenience sampling, 11 experts (herein denoted as E1 through E11) were recruited to participate in the study reported in this paper. The recruitment of the participants was accomplished in two phases. In the first phase, I sent out invitation emails to calculus instructors I know in the United States. One of the experts was my colleague at the same institution I was working for at the time of the study, another expert was from an institution I was previously affiliated with, some experts are colleagues I met at academic conferences, and yet other experts are colleagues in the teaching profession that I do not know at a personal level, but I am familiar with work they had done related to the teaching and learning of calculus through their scholarly works. In the second phase, I searched the internet using key words such as "calculus coordinator" or "calculus director." I then sent out an invitation emails to participate in the study to anyone whose contact information (email) was listed as a calculus coordinator/director in a mathematics department in the United States.

In total, I sent out a total of 14 invitations. Of these invitations, 11 experts agreed to participate in the study. Only two of the 11 participants partially completed the questionnaire with an 82% completion rate-the rest of the participants completed all the items included in the questionnaire. Three participants had taught 1-5 sections, two participants had taught 6-10 sections, one participant had taught 11-15 sections, one participant had

taught 16-20 sections, and four participants had taught over 20 sections of Calculus I sections, respectively. Furthermore, eight participants were affiliated with R1 institutions i.e., institutions with a very high research activity, two participants were affiliated with R2 institutions i.e., institutions with a high research activity, and one participant was affiliated with liberal arts college i.e., an institution with a moderate research activity.

3.3 Data analysis

Thematic analysis was used to analyze data for the study i.e., experts' responses to Items 3 through 11 in the questionnaire. According to Braun and Clark (2006), thematic analysis is "...a method for identifying, analysing and reporting patterns (themes) within data" (p. 79). The term theme, as used in this study, refers to a common response to the questionnaire items given by at least two experts. For instance, if one expert noted cost, another expert mentioned revenue, and another expert remarked about profit in response to Item 8 in the questionnaire that elicited experts' perceptions regarding typical real-world contexts the experts use in their teaching of optimization problems in Calculus I, I identified the economics context as a theme.

4. Results

4.1 Students' strengths and weaknesses when working with optimization problems

Performing algebraic manipulations and solving simple problems: In response to Item 3 in the questionnaire that was used to elicit experts' views regarding students' strengths when working with optimization problems, nine of the 11 experts interviewed in this study remarked that performing algebraic manipulations (e.g., calculating derivatives) and solving simple problems is often straightforward for most students. The following is a reproduction of exemplary responses:

Students have found the process of differentiating an optimizing function [the function whose maximum or minimum value is sought] straightforward. At that point, they are pretty good at differentiating so doing the calculus of the optimization problem isn't difficult for them (E4).

Performing algebraic manipulations (e.g., differentiation), especially once they have found the relevant equations in a given scenario (E5).

Taking the derivative [of the optimizing function], Setting the derivative equation to zero, and solving. These steps are always the same for any optimization problem, and students have a lot of experience with finding derivatives by then (E8).

Farmer-type problems (i.e., find the largest-area pen that you can build with this amount of fence). Also, straight numerical problems, like "find the absolute min and max of this function on this closed interval." (E2).

The very simple problems involving area of a rectangle/perimeter of a rectangle (E7).

A careful examination of E4, E5, and E8's responses suggest that calculating derivatives, once the objective function (also known as the optimizing function) has been determined (if not given), is easy for most students when working with optimization problems. Taken together, E2 and E7's responses suggest that solving area maximization/minimization problems involving rectangles is generally well understood by students. It should be noted that although E2 did not specifically mention the word "rectangle" in his response, farmer-type problems are common and standard problems that are covered in most, if not all, calculus classes or textbooks in the United States. Furthermore, farmer-type problems generally involve working with rectangles (cf. LaRue & Infante, 2015).

Mathematizing word problems: In response to Item 4 in the questionnaire that was used to investigate experts' perspectives regarding students' difficulties when working optimization problems, all the experts made remarks that suggested that translating prose to text i.e., mathematizing (Freudenthal, 1993) these type of problems is a common challenge for many students. The following is a reproduction of a few exemplary responses given by some of the experts:

Most of it. :-) 1.) Coordinating all of the pieces in a big problem is hard for students. They often get lost in the details and forget the

big ideas. 2.) Setting up the optimization problem is often hard for students (although for some reason, I think my students did pretty well with this this semester). 3.) Algebra can also be tricky. They know to set the derivative equal to 0, but they don't always know how to solve for x (algebraically). 4.) They often forget to use the first or second derivative test to determine if their critical value really gives the optimal value. I'm not sure they realize why this is a big deal (E1).

Word problems that aren't farmer problems, or that require understanding of the physical situation to set up the objective function [synonym for optimizing function], or where the feasible interval isn't bounded, or where the objective function involves angles. Examples include things like: A train starts at P1 and is traveling north at α mph, and a truck starts at P2 and is traveling east at β mph. Or, my favorite: Given a circular metal disk of radius 10, you want to cut one sector of angle θ and weld the edges together to make a cone. What angle θ gives the cone of largest volume (E2)?

One of the challenging parts of optimization problems for students seems setting up the initial variables and translating given problem into math problems. The other challenging part seems explaining logically why at certain position it could have the optimized results using either the first derivative or second derivative test. A lot of students forget that part, and simply assuming that the optimization happen at any critical number they found (E10).

E1, E2, and E10 all commented on students' difficulties associated with setting up the optimizing function when working with word problems. However, only E1 and E10 noted that verifying extrema i.e., using the first or second derivative test to check if the critical value(s) they found would result in the optimal value(s) for the optimizing function is generally problematic for calculus students. Additionally, E1 and E7 are the only experts who remarked that sometimes students' difficulties with solving optimization problems stem from lack of facility with working with complex algebra, especially when trigonometric functions are involved.

4.2 Effective ways to help students become proficient at solving optimization problems

Encourage students to construct and use diagrams: In response to Item 5 in the questionnaire that prompted experts to comment on effective ways they have used to support students' learning about optimization problems, three experts emphasized the importance of drawing and using diagrams that serve as visual illustrations of the scenarios described in these problems. The following is a reproduction of these experts' responses to Item 5 in the questionnaire:

I always tell students to draw a diagram of the object/scenario they wish to optimize and label appropriate quantities. This can help them to realize the formula for the appropriate geometric shape. (E4).

For interpreting problems, I have often found it useful to encourage students to draw and label diagrams whenever possible to help them visualize the relationships (E5).

I always encourage them helping each other, drawing pictures, and leveraging all of their resources that they have online or in-person (E6).

Although E6 did not provide a rationale for encouraging students to draw diagrams when solving optimization problems, from E4 and E5's responses one could infer that the purpose of drawing and using diagrams is to help students make sense of the quantities and relationships among the quantities involved in these problems. In other words, the purpose of these diagrams is to support students' quantitative reasoning while working on these type of problems (cf. Smith III & Thompson, (2007; Thompson, 1993; Thompson, 2011).

Provide a set of steps students could follow: In response to Item 5 in the questionnaire, five experts made remarks to the effect that they provide students with a set of steps students could follow when solving optimization problems. The following is a reproduction of some exemplary responses to the aforementioned questionnaire item:

We often talk through the big ideas (generally) without doing all of the steps. I also give them several problems to solve (many of which are graded). (E1).

I give them a step by step process, that involves writing the objective function (including realizing that they are wrong if their function has more than one variable), defining the feasible interval, finding critical points, and proceeding from there (E2).

We focus first on what quantity we are trying to maximize or minimize. We set up an equation to represent that quantity, and then we ask ourselves if the equation we have written down describes our exact problem (for example, if we know our rectangle is supposed to have an area of 400cm^2 , then is that information incorporated into our function?) We do several problems where they *only* set up the function. This allows for more practice and experience setting up the [optimizing] function (E7).

I tell them that the construction of objective function proceeds in two steps: (1) finding a formula for the quantity to be maximized/minimized; often it is a known geometric formula that should be memorized. (2) reducing the number of variables to 1, if there are more than 1. This requires one to express the relation between different variables as an equation, and to use it to eliminate one of the variables (E9).

A close examination of the preceding responses reveals that while E1 and E2 provide a set of steps for solving optimization problems in general, E7 and E9's responses suggest that these experts provide steps that are specific to constructing the optimizing function. Indeed, constructing the optimizing function is particularly challenging for most calculus students when working with optimization problems based on the evidence provided in Section 4.1.

Individual and group practice problems: In response to Item 5 in the questionnaire, three experts noted that they provide numerous individual and group opportunities for students to practice working with optimization problems. The following is a reproduction of these experts' responses to Item 5 in the questionnaire:

We often talk through the big ideas (generally) without doing all of the steps. I also give them several problems to solve (many of which are graded). (E1).

It is important to show the students that they are capable of doing these problems on their own. Thus, I tend to give them a lot of "easy" optimization problems to try on their own first before I move on to more difficult examples. I also give them plenty of opportunities for practice. This includes in-class and outside-of-class worksheets (E8).

Examples, group quizzes in class (E11).

Arguably, the use of graded assignments on optimization problems as E1 does, encourages students to put in maximum effort when working on these assignments and not just to complete them for the sake of completing an assignment. While E1 was not specific whether these assignments are completed in the classroom or outside the classroom, E8 specifically noted that the opportunities he provides takes place both during classroom instruction and outside the classroom. Unlike E1 and E8 who were not specific on whether the assignments they provide are to be completed individually or in groups, E10 specifically mentioned that he gives students group quizzes during classroom instruction. Because effective instructional approaches are the central focus of this paper, I have reproduced all the experts' responses to Item 5 in the questionnaire in Appendix B. Readers will observe that although the suggested teaching approaches in the aforementioned appendix are not necessarily themes, they are indeed worthy of consideration when teaching optimization problems, especially for novice calculus instructors.

4.3 Educational technologies and tools in the teaching of optimization problems

In response to Item 6 in the questionnaire, which I used to elicit experts' views regarding technological tools they use to support students' learning about optimization problems in Calculus I, seven experts indicated that they use several educational technologies, including Desmos, GeoGebra, WebAssign visuals, or a combination of these technological tools. The following is a reproduction of five exemplary responses to Item 6:

WebAssign and Crowdmark for HW assignments. Sometimes (rarely) we will graph the optimizing function and talk about what values mean (E1).

I try to use visuals from GeoGebra and WebAssign (E3).

I call on Desmos for technology in optimization. The optimization functions are often difficult to visualize, so use of Desmos can enable students to verify their result graphical (e.g. is the answer they got truly a local minimum/maximum). (E4).

I often use graphing tools like desmos and GeoGebra to help students generate graphs. Geogebra is especially very good because you can create animations and moving sliders that students can adjust to see various relationships and how variables change in real-time (E5).

Sometimes we use graphing utilities like Desmos to graph the function and look at the maximum/minimum to see if it matches what we found algebraically. It's also helpful with the rare problems where there is more than one critical point and we have to figure out which one gives the actual absolute maximum or minimum in the specific domain (E7).

While experts like E1 and E3 only mentioned technological tools they use to support students' learning about optimization problems without discussing the rationales or reasons for using these technologies, experts like E4, E5, and E7 provided detailed responses. E4, for example, uses Desmos to help students graph and visualize optimizing functions. Furthermore, E4 further remarked that the "...use of Desmos can enable students to verify their result graphically (e.g. is the answer they got truly a local minimum/maximum)?" It should be noted that three other experts expressed that they do not use any technological tool in their teaching of optimization problems. In fact, one of these experts expressed interest in learning to use technology in teaching of optimization problems as can be seen in the following excerpt: "I currently do not use technologies to teach optimization problems. But I would be interested in learning how one could supplement their teaching of optimization problems with technology." (E8).

I thus hope that the information presented in this section regarding various technologies used by other experts, how or why they use these technologies will serve as a great starting point for experts like E8 who are interested in learning about integrating technological tools in their teaching of optimization problems in calculus.

In response to Item 7 in the questionnaire, which I used to examine experts' views regarding non-technological tools they use to support students' learning about optimization problems in Calculus I, three experts mentioned providing ample opportunities for students to work with optimization problems in and outside the classroom. These experts' responses are in many ways similar to those discussed in Section 4.2. Consequently, I chose not to reproduce them in this section. Instead, I reproduced all the experts' responses to this item in Appendix C. I further note that, although there are no other themes (besides providing ample practice problems) in the experts' responses to Item 7 in the questionnaire (Appendix C), most of the responses offer valuable insights on effective teaching approaches related to the teaching of optimization problems in Calculus I. As can be seen in Appendix C, four experts provided responses that suggest that they do not use any special non-technological tools in their teaching of optimization problems in Calculus I.

4.4 Typical real-world contexts used by experts in the teaching of optimization problems

In response to Item 8 in the questionnaire, which I used to examine experts' views regarding typical real-world contexts they use in their teaching of optimization problems in Calculus I, seven experts noted that they often use economics and kinematics contexts, respectively. The following is a reproduction of exemplary responses to Item 8 in the questionnaire:

Economics (minimizing cost) kinematics (?) (We have problems where we minimize the time to get to a point, or finding the maximum acceleration, etc.) perimeter/area to maximize space or minimize perimeter I'm sure I'm missing several. Most of these seem to be "real-world" contexts (E1).

We do use economics, but since I teach the Calc 1 class for physical science and engineering, most of the examples are physical. They

involve finding things like the least cost road that can be built with some combination of bridge and surface roadway, or the shortest board that can be placed with some geometric constraint, or the minimum distance between two moving objects, etc. We have a separate calc 1 class that is more oriented toward business, econ, and social science, and that's not the one I usually teach (E2).

While the question mark (?) in front of the word kinematics in E1's response may be taken to mean that this expert was not sure about whether or not she uses optimization problems that would qualify as having a kinematics context in her teaching of Calculus I, her claim that some of the problems she uses involve finding the maximum acceleration provides evidence of using a kinematics context. A kinematics context, in my understanding is one that involves the concepts of distance, position, velocity, speed, and acceleration. E2's claim that most of the examples he uses in his teaching of Calculus 1 are physical such as finding the "...minimum distance between two moving objects" provides evidence of using kinematics contexts in his teaching of optimization problems.

4.5 Strengths and weaknesses in the presentation of optimization problems in calculus textbooks

Before delving into the experts' views regarding strengths and weaknesses in how calculus textbooks they have used present optimization problems, I would like to note that nine of the 11 textbooks used by the 11 experts in this study were authored by James Stewart, a well-known calculus textbook author in the United States. One of the other two textbooks was authored by Matthew Boelkins while the other textbook was authored by three authors, namely Joel Hass, Christopher Heil, and Maurice Weir. The aforementioned summary on the calculus textbooks used by the experts who participated in this study is based on information obtained from the experts' responses to Item 9 in the questionnaire, which I used to gather details about calculus textbooks used by the experts in their teaching of optimization problems in Calculus I. The details include textbook names, authors, and edition, respectively.

In response to Item 10 in the questionnaire, which I used to examine experts' views regarding weaknesses in the presentation of optimization problems in calculus textbooks, three experts expressed disappointment that the examples or practice problems provided in calculus

textbooks are not realistic. The following is a reproduction of the three experts' responses to Item 10 in the questionnaire:

The main issue I see is that some books get a little too exotic with the geometry, or use physics examples that are too abstract (e.g., luminance, electromagnetism). (E2).

There are rather standard problems that students do not view as real-life applications (E3).

Most "real-life" optimization problems are real "fake real-life" optimization problems. For example, no one is going to calculate how far one needs to run before swimming to an island to optimize the time spent on traveling (E8).

E2 noted that some of the optimization examples given in calculus textbooks are abstract, while E3 noted that optimization problems provided in calculus textbooks are generally not viewed by students "as real-life applications", perhaps because they are often abstract or have a camouflage context. E8 not only remarked that optimization problems in calculus textbooks have unrealistic contexts, but also went on to provide an example of one such problem i.e., calculating how far one needs to run before swimming to an island to optimize the time spent on traveling. Two other experts lamented that solutions to most optimization examples and practice problems provided in calculus textbooks are easily accessible to students via the internet. In response to Item 10 in the questionnaire, E11 commented, "Solutions to HW [homework] are everywhere online..." (E11). In response to the same item, another expert remarked, "many of the problems have been recycled over years and years, and as such the solutions are readily available to students on external resources such as Chegg [An American education company that provides many services, including step by step solutions to practice problems]" (E4). Remarking on a creative approach to alleviate the severity of this weakness in calculus textbooks' presentation of optimization problems, E4 added, "this forces me and other instructors to write novel questions on optimization (e.g. cats and their play pens)." Two other experts stated that they could not think of any weakness regarding the presentation of optimization problems in calculus textbooks they have used.

In response to Item 11 in the questionnaire, which I used to examine experts' views regarding strengths in the presentation of optimization problems in calculus textbooks, five experts expressed appreciation for the abundance of optimization examples and practice problems provided in calculus textbooks. The following is a reproduction of three exemplary responses to Item 11 in the questionnaire:

I like how, active Calculus specifically, uses relatable real-life situations in presenting optimization problems. The text also provides some questions that students explore before they encounter the concept of optimization. Many texts have several solved examples on optimization problems and several exercises for students to try. This, I think, is a strength (E5).

Lots of examples for students to see (E6).

Many examples and problems for students to try on their own (E8).

While E6 only remarked on the abundance of optimization examples as a strength for calculus textbooks, E5 and E8 remarked on the abundance of optimization examples and practice problems, respectively. Two other experts did not respond to this item, perhaps because they could not think of anything in particular they could attribute as a strength in how calculus textbooks present optimization problems. Although not a theme, one expert noted that there was nothing he could note as a strength: "Most are pretty standard, and nothing stands out as a strength." (E2). E2 elaborated, "reading about this topic [optimization problems] is very dry for students, so there's no substitute for covering it in a class." Another expert expressed appreciation for the graphics used by calculus textbooks in their presentation of optimization problems as can be seen in her response: "There are usually some good graphics, and they include the graph of the [optimizing] function a lot of the time." (E7).

5. Discussion and Conclusions

In what follows, I discuss the main findings of the study. First, based on the experiences of a majority of the experts in this study, performing algebraic manipulations such as calculating derivatives of optimizing functions and finding critical values of these functions is generally well

understood by students. On the contrary, several studies have reported that finding critical numbers is sometimes challenging for calculus students (cf. Brijlall & Ndlovu, 2013; Dominguez, 2010; Mkhathshwa, 2019; Swanagan, 2012). The experts further noted that solving application problems involving optimization problems is typically difficult for students. Particular difficulties exhibited by students when solving application problems include but are not limited to formulating the optimizing function and verifying extrema (i.e., showing, using the first or second derivative test, to show that a particular critical value yields the optimal value for the optimizing function) is particularly challenging for most calculus students. The experts' observations regarding students' difficulties when tasked with solving optimization problems are consistent with findings of previous research on students' thinking about optimization problems in Calculus I (cf. Borgen & Manu, 2002; Klymchuk et al., 2010; Mkhathshwa, 2019; Swanagan, 2012; Villegas et al., 2009; White & Mitchelmore, 1996).

Second, all the experts in this study remarked on several effective teaching approaches they have used to support students' learning about optimization problems in Calculus 1. These approaches include, but are not limited to *encouraging students to construct and use diagrams (when it makes sense) when working with optimization problems, providing a set of steps that could serve as a guideline for students when solving optimization problems, and creating ample individual and group opportunities for students to practice solving a wide range of optimization problems during course lectures as well as outside the classroom*. A complete list of the teaching approaches used by the 11 experts are reproduced in Appendices B and C. Additionally, most experts endorsed the use of educational technologies like Desmos, GeoGebra, and WebAssign to facilitate understanding. They highlighted how these tools can aid in visualizing optimizing functions and verifying solutions. The interested reader is encouraged to consider the work of Arango et al. (2015) and Çekmez (2021) as examples on how one of these technologies (GeoGebra) could be used in the teaching of optimization problems in calculus. As an experienced calculus instructor myself, I strongly recommend adopting most if not all of the suggested teaching strategies and technologies suggested by the experts in the teaching of optimization problems and other concepts such as the derivative in Calculus I. While these teaching strategies and technological tools could work for nearly any calculus instructor, they can be

especially helpful for novice calculus instructors such as graduate teaching assistants in mathematics departments.

Third, it is commendable that most of the experts noted using other another real-world context (economics), in addition to the kinematics context in their teaching of optimization problems in Calculus I. Findings of previous research on students' thinking about concepts (e.g., derivatives) directly related to optimization problems indicate that such concepts are typically well understood in kinematics contexts and that projecting these concepts to other real-world non-kinematics contexts is generally difficult for students (cf. Ibrahim & Rebello, 2012). In fact, recent research (Mkhatshwa, 2022) on examples and practice problems on derivatives provided by one of the commonly used calculus textbooks in the United states indicate that these examples and practice problems are dominated by a kinematics context. Additionally, several of the experts in this study expressed disappointment that a majority of the examples and practice problems on optimization provided in calculus textbooks they have used have a camouflage context, and consequently are not interesting to students. Some experts further noted that these examples and practice problems are fairly standard and found in most calculus textbooks. Consequently, solutions to these examples and practice problems are easily accessible to students online via platforms such as Chegg. On a positive note, nearly half of the experts in this study expressed appreciation for the multitude of optimization examples and practice problems provided in most calculus textbooks. To this end, I recommend that calculus instructors and textbook selection committees in mathematics departments consider several things when adopting/selecting calculus textbooks for their courses. Examples of things to consider include opportunities to work with optimization problems (and other topics in calculus in general) that have several real-world contexts, opportunities to work with a variety of examples and practice problems (i.e., standard and non-standard), and opportunities to work with examples and practice problems that are more realistic in nature to promote interest to learn about these problems among students.

6. Study Limitations and Potential Areas for Future Research

I would like to note that while the results reported in this study are quite informative and potentially helpful for many calculus instructors, especially novice instructors such as graduate teaching assistants in

mathematics departments, the fact that the experts in this study were not interviewed represents a limitation. Specifically, conducting structured interviews could have provided opportunities for the experts to elaborate in greater detail regarding how they use certain strategies or technologies to support students' learning about optimization problems. This could be a subject for future research. To alleviate this concern, a majority of the experts provided sufficient details in their responses to the questionnaire items, especially to the items about effective teaching strategies and technologies related to the teaching of optimization problems in Calculus I. Furthermore, the interested reader is specifically referred to, in the Discussion and Conclusions section of the paper, to consider the works of several scholars (cf. Arango et al. 2015; Çekmez (2021) for examples on how to incorporate one of the technologies (GeoGebra) used by several experts in this study to support students' learning about optimization problems.

The data reported in the current study was analyzed by one researcher. Consequently, it was not possible to measure the inter-rater reliability of the questionnaire used in the study. I recommend that future research that uses the questionnaire used in the current study (or its adaptation thereof) also measures the inter-rater reliability of the questionnaire, in addition to assessing the face and content validity of the same instrument. I strongly recommend that future research examines the effectiveness (or lack thereof) of the teaching strategies documented in the current study in different instructional settings or with different student populations. Lastly, I remark that the fact that the sample size (11 participants) is small and that the survey respondents were not randomly selected limits the extent to which the results of the study could be externally valid i.e., generalized to other settings.

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Appendix A-Questionnaire

1. According to the Carnegie Classification System, what is the rank (e.g., R1) of the institution you are affiliated with?
2. How many sections of Calculus I have you taught?

1 to 5	6 to 10	11 to 15	16 to 20 over 20
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3. Drawing on your experience teaching calculus I, what have you found to be easy/straightforward for students when working with optimization problems? Explain.
4. Drawing on your experience teaching calculus I, what have you found to be particularly difficult/challenging for students when working with optimization problems? Explain.
5. What are some of the effective ways you have used to help students overcome challenging/difficult steps involved in solving optimization problems in your Calculus I classes? Explain.
6. What teaching technologies, if any, do you use to support students' learning about optimization derivatives in your Calculus I classes? How do you use these technologies? Explain.
7. What other tool(s), besides technology, do you use to support students' learning about optimization problems in your Calculus I classes? How do you use this tool(s)? Explain.
8. What real-world contexts (e.g., economics), if any, do you typically use in your teaching of optimization problems in your Calculus I classes? Explain.
9. Please state the title, author(s), and edition (if applicable) of the calculus textbook you have used in your recent teaching of Calculus I.
10. What do you consider to be a weakness(es), if any, in how Calculus I textbooks you have used present optimization problems (e.g., in expository sections, examples, or exercises, respectively)? Explain.
11. What do you consider to be a strength(s), if any, in how Calculus I textbooks you have used present optimization problems (e.g., in expository sections, examples, or exercises, respectively)? Explain.

Appendix B
Effective strategies for teaching optimization problems in calculus

Table 1. Experts' responses to Item 5 in the questionnaire

Expert	Response to Item 5- What are some of the effective ways you have used to help students overcome challenging/difficult steps involved in solving optimization problems in your Calculus I classes? Explain.
E1	We often talk through the big ideas (generally) without doing all of the steps. I also give them several problems to solve (many of which are graded).
E2	I give them a step by step process, that involves writing the objective function (including realizing that they are wrong if their function has more than one variable), defining the feasible interval, finding critical points, and proceeding from there.
E3	I try to provide step-by-step guidelines to break the problem into manageable steps.
E4	I always tell students to draw a diagram of the object/scenario they wish to optimize and label appropriate quantities. This can help them to realize the formula for the appropriate geometric shape.
E5	For interpreting problems, I have often found it useful to encourage students to draw and label diagrams whenever possible to help them visualize the relationships.
E6	I always encourage them helping each other, drawing pictures, and leveraging all of their resources that they have online or in-person.
E7	We focus first on what quantity we are trying to maximize or minimize. We set up an equation to represent that quantity, and then we ask ourselves if the equation we have written down describes our exact problem (for example, if we know our rectangle is supposed to have an area of 400cm^2 , then is that information incorporated into our function?) We do several problems where they *only* set up the function. This allows for more practice and experience setting up the function.

E8	It is important to show the students that they are capable of doing these problems on their own. Thus, I tend to give them a lot of "easy" optimization problems to try on their own first before I move on to more difficult examples. I also give them plenty of opportunities for practice. This includes in-class and outside-of-class worksheets.
E9	I tell them that the construction of objective function proceeds in two steps: (1) finding a formula for the quantity to be maximized/minimized; often it is a known geometric formula that should be memorized. (2) reducing the number of variables to 1, if there are more than 1. This requires one to express the relation between different variables as an equation, and to use it to eliminate one of the variables.
E10	Honestly, I do not have any specific effective ways to help students to overcome those steps other than (1) explain why those steps are important and (2) explain with other examples those mistakes could cause wrong answers.
E11	Examples, group quizzes in class.

Appendix C

Additional effective strategies for teaching optimization problems in calculus

Table 2. Experts' responses to Item 7 in the questionnaire

Expert	Response to Item 7-What other tool(s), besides technology, do you use to support students' learning about optimization problems in your Calculus I classes? How do you use this tool(s)? Explain.
E1	I provide lots of class time for students to work on problems in groups. I also provide access to several videos (that we made during Covid) that shows the set up and sometimes the full solution to several of these problems. I encourage them to try them on their own before watching the videos.
E2	Nothing I'd call a tool. I'm not sure what a tool would look like for this kind of question. Even though these problems are often visual and physical, I can't think of any way to do them other than to learn to set them up on paper.

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- E3 GeoGebra has many visual apps to provide understanding of the problems.
- E4 In-class activities I use are carefully designed to guide them through an example (usual lecture), then they practice a similar example but with the constraint and optimizing function reversed. E.g. I show them how to maximize volume for a fixed surface area, then they are tasked to minimize surface area given a fixed volume.
- E5 Sometimes I use real objects in my classes and have students manipulate them before we move on to Technology tools. Many students care about how the mathematics they are learning can be applied in real life so I find it helpful to demonstrate some of the real-life scenarios in my classroom. The popular oil spill problem for example, can be easily demonstrated in class using a large water container and oils of varying viscosity.
- E6 I haven't really used other tools.
- E7 If the problem involves in geometry, we always draw and label the shape.
- E8 I use in-class and outside-of-class worksheets. We also have recitation where students get extra practice on optimization problems.
- E9 None
- E10 No special tools.
- E11 Gradescope.com is a good technology. It allows graders to send scores more immediately to students and allow students to more directly and freely argue for points back to the specific graders (anonymously).
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Gen Z - Know them, Reach them, Recruit them, and the Consequences Should We Fail

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The first-generation members of Gen Z, once on track to become the most educated cohort in history, have veered off course, with many now pursuing alternative paths. This alarming shift in trajectory necessitates our immediate attention. In this paper, we aim to introduce scholars and practitioners to Gen Z, illuminate potential causes for this shift, propose recruiting methods aligned with generational preferences, and outline the potential consequences if this trend persists. The implications for the U.S. economy and Gen Z members without a college degree could be severe. However, there is still a window of opportunity, as nearly half of this cohort is still in grade/high school. The authors present alternative career paths and strategies to engage Gen Z.

Introduction

As Baby Boomers and Generation X age out and exit the workplace, many institutions and industries have done little to prepare for the coming shift in the workforce. Generation Y, or Millennials, have become the largest part of the workforce and moved into leadership roles. Generation Z, or Gen Z, is just starting to make career choices and move into the workplace with very different expectations. Considering institutions and industries will rise and fall with this incoming cohort, it is essential to understand what sets them apart from previous generations.

The disruptive nature of the COVID-19 pandemic forced colleges and universities to transform to meet the needs of their students quickly; however, the bureaucracy of higher education generally prevents academic institutions from having the agility required to match industries' workforce needs, take advantage of federal funding opportunities, and meet Gen Z's need for real-world skills directly tied to a career path. Agile colleges and universities adapt and respond not only quickly but proactively by adopting

policies and procedures that allow them to take advantage of resources as they become available, and modify existing programs, or add programs that prepare students through workforce development opportunities and understanding employment needs (McCully, & McDaniel, 2007; Baim, 2019; Qtairi & Alshoraty, 2022; Hoyt & Jones, 2023).

Although the dates for identifying Gen Z vary from study to study, Fry and Parker (2018) offer that Gen Z includes people born from 1995 to 2015. They further note that this is a racially diverse, large generation (52% non-Hispanic white and 20% of the population); additionally, Della Volpe (2022) found Gen Z has strong feelings about social, environmental, and political issues. However, many Gen Z are opting out of post-secondary education and struggling to find a career path. A generation without education is disastrous to the U.S. economy and potentially to each cohort member. Fortunately, a significant portion of this cohort is still in middle and high school, so there is still time to act.

Post-Secondary Educational Expectations and Gen Zs' Concerns

Gen Z sees the purpose of education as to prepare them, in very practical ways, for life after high school – and yet, overwhelmingly, they feel like their K-12 education did not prepare them adequately to enter today's world (Della Volpe, 2022). This cohort appreciates a more practical try-it-and-see approach to learning, unlike the sit, listen, and trust authority mentality of generations past (Gelford & Kahl, 2014; Bhandarker & Kumar, 2017; Ortiz & Redmon, 2020; Mahesh et al., 2021).

Gen Z is the first generation to grow up with smartphones and have always known the internet. Therefore, access to technology has changed their outlook on the value and cost of education (Stancampiano, 2022). A recent two-year Question the Quo survey (2022) of 5,317 Gen Z high schoolers (ages 14–18) found that Gen Z wants shorter, more affordable, career-connected education pathways in high-demand industries. The survey, which measured pre- and post-Covid Gen Z mindsets, found that the number of students considering a four-year college education dropped nearly 20 percentage points from February 2020 to January 2022. This study found that 62% of those surveyed wished their high schools had provided more information on post-secondary career paths. In addition, there was almost a 10-point drop in those who believed any post-secondary education was necessary. The study found that the top criteria for choosing a path after high school included only considerations about cost and whether

college would provide skills to help them earn a higher wage. Unfortunately, higher education lacks the agility to pivot and offer programs that utilize federal funding, match workforce needs, and meet Gen Z's need for real-world skills directly tied to a career path.

Higher Education's Concerns about Gen Z and Beyond

Looming large in higher education's not-too-distant future is the great 'demographic cliff' of 2026. In 2026, the number of high school graduates in the United States will peak and then steadily and rapidly decline, leading to a drop in college enrollment (Selingo, 2021). Pre-Covid Gen Z college enrollment rates were significantly higher than previous generations; however, enrollment dropped with 2019 and 2020 graduating classes by almost seven percent (Selingo, 2021). Additionally, the number of international students may slow due to immigration laws (Selingo, 2021). Therefore, it is imperative that colleges recruit and retain Gen Z. To recruit them, we must understand their formative experiences and values.

The Pandemic

The most significant event affecting Gen Z would be the Covid-19 global pandemic. As a result, post-pandemic Gen Z is sometimes referred to as "Generation Resilient," particularly those 18 to 28, who comprise emerging adulthood (Arnett, 2000). Emerging adulthood is "a time of life when many different directions remain possible, when little about the future has been decided for certain, when the scope of independent exploration of one's life's possibilities is greater for most people than it will be at any other period of the life course" (Arnett, 2000, p. 469). Both professionally and personally, this is when young people lay the foundation for adult life. However, there is a real sense of urgency to make up for lost time because many Gen Z feel cheated out of two years of their lives, having missed experiences, friendships, and milestones (Paz, 2021). Unfortunately, the pandemic significantly reduced the opportunities available to high school and college graduates, forcing many to settle for lower-paying jobs to pay their bills (Paz, 2021). Many Gen Z's are finding creative ways to make extra money (like reselling clothes, DIY crafts, and innovative freelance services) to compensate for the income gap (Merriman et al., 2022).

A Nation Divided

The Harvard Public Opinion Project (HPOP) has been surveying 18 to 29-year-olds since 2000 to gain insight into young people's attitudes toward politics and public service. Gen Z will soon be the country's largest cohort of eligible voters – and they do plan to vote – giving them tremendous power (40.8 million eligible voting members) to remake institutions in ways that support their vision for the future (Deckman et al., 2020; Della Volpe, 2022; Medina & Suzuki, 2023). The results of the 2022 survey found that young people are turning out to vote. In addition, being raised in a tumultuous America has given Gen Z a distinctive sense of personal and public purpose (Della Volpe, 2022). Negative partisanship helped Gen Z to form opinions based on the actions of a party they disliked; our culture and our society evolve when the passion of young people melds with the power of those leading our institutions (Della Volpe, 2022). They are the most educated and least prejudiced cohort; Gen Z voted in historic numbers in 2022 to address the climate crisis, gun violence, personal rights and freedoms, and student debt relief (Deckman et al., 2020; Della Volpe, 2022).

Interestingly, the Pew Research Center (2024) found a correlation between higher education and political affiliation. The study reports that 52% of registered voters with a high school diploma or less favored the Republican party; however, registered voters with a college degree (51%) and postgraduate degree (61%) identify as Democratic (Doherty et al., 2024). Additionally, Hohagen and Bitar (2024) propose young American males are shifting to the right, citing dissatisfaction with the economy (inflation), climate policies, and a failure to resolve ongoing global conflicts for the shift. These authors also suggest some Gen Z voters are considering third-party candidates due to frustration with the two-party system (Hohagen & Bitar, 2024).

The Gender Gap

In 2024, of the total number of bachelor's degrees awarded, 58.4 % were conferred to women compared to 41.5% to men, and females are 32% more likely to finish their degree at the institution of their choice than men (Hanson, 2024). Gen Z women voted for Democrats, although the percentages (49% white, 85% black, and 65% Latino) varied greatly depending on race (Medina et al., 2025). According to Munroe (2024), one of the reasons Gen Z male voters are conservatively leaning is masculinity and the need to take back our country. Further, a Pew Research Study

(2024) found that 1 in 5 men feel the gains women have made over the last decade have been at the expense of men (Horowitz & Parker, 2024). Many young men think nostalgically about the days when men were perceived to be more valuable (Munroe, 2024). The "Make America Great Again" slogan spoke to many Gen Z males who admired Donald Trump's strength, viewing him as a hero who would take down the ruling Democrats and restore pride to masculinity (Munroe, 2024).

Social Justice

According to the 2022 HPOP (The Harvard Opinion Pole, 2022) survey, only 33% of Gen Z trust the Supreme Court. This is a 10%-point drop in five years as it was 44% in 2018. An anti-establishment narrative began to develop with the oldest Gen Z in September 2011 when the Occupy Wall Street movement started to protest economic inequality (Della Volpe, 2022). Occupy Wall Street was one of several social justice events to shape how Gen Z sees its role in improving the future (Della Volpe, 2022). Donald Trump's presidency, George Floyd's murder, the Parkland School shooting, and Greta Thunberg's School Strike for Climate are the other events that are interwoven to shape Gen Z's attitudes, opinions, and beliefs on social justice (Della Volpe, 2022). Deckman et al. (2021) suggest the Women's March of 2017 and the # MeToo Movement also shaped Gen Z's political views. Through social media, Gen Z has been exposed to and feels connected with the climate and their peers around the globe. Unlike Boomers and Gen X, whose world was their neighborhood, for Gen Z, thanks to the internet, the world is limitless, which brings empathy and understanding (Deckman et al., 2021; Della Volpe, 2022). However, the downside of having access to the infinite world of the internet is viewing the world's woes at a young age and lacking the maturity to mentally comprehend all materials being considered.

Emotional Health and Well-being

Gen Z is reporting higher levels of anxiety, depression, and distress post-Covid than any other generation (Coe et al., 2022). According to the World Health Organization, social determinants of health (SDoH) are the non-medical factors influencing health outcomes; they are the conditions in which people are born, grow, live, work, and age. A Kaiser Family Foundation survey (Drake & Rudowitz, 2022) found that 69.9% of Gen Z survey respondents perceived they had unmet social needs. Therefore, as Gen Z develops their resilience, they may expect holistic wellness programs

that include physical health, behavioral health, and social needs as potential students, employees, and customers (Coe et al., 2022).

Social Media

Gen Z are avid social media users; they use it to guide social change, challenge political institutions and governments, and hold the corporate world accountable (Reinikainen et al., 2020). Savvy corporations have tapped into the Gen Z market with a strategy known as 'corporate social advocacy' or 'corporate activism,' which suggests a higher pursuit beyond economic gains (Reinikainen et al., 2020). Coe et al. (2023) found that one-third of Gen Z survey respondents (n=16,824) spent more than two hours on social media daily. Among Gen Z social media users, the preferred platforms are in descending order: YouTube (88%), Instagram (76%), TikTok (68%), and Snapchat (67%). Perhaps the best example of this strategy is Nike's 'Dream Crazy' advertising campaign in 2019, in collaboration with Colin Kaepernick. This NFL player took a stand against police brutality and racial injustice (Reinikainen et al., 2020). This kind of 'mobilizing talk' raises societal awareness and invites consumer discussion and action, thereby blurring the line between emotional issues and corporate brands (Olkkonen & Jaaskelainen, 2019). Further, Gen Z are avid social media users who want to obtain skills and education in their areas of interest, according to YouTube's *Culture & Trends Report 2022* (Roberts, 2023).

What Success Looks Like to Gen Z

Over the last ten years, Gen Z has seen divisive politics, economic instability, mounting social injustice, a global pandemic, and the exponential melting of the polar ice caps (Merriman, 2022). Still, instead of passively watching the world crumble, they want to take control of their future with their choices around education, work, and society (Merriman et al., 2022). Although previous generations measured success extrinsically (high-profile careers, money, fame), Gen Z values meaningful work, financial stability, and a life full of meaningful experiences (Morris & Hedges, 2024; Merriman et al., 2022). Boomers, Gen X, and Y focused on building traditional careers and wealth; Gen Z focused on earning enough to secure financial stability and not something that gave meaning and purpose to their lives (Mahesh et al., 2021; Merriman et al., 2022). Many Gen Z actively try to limit spending (63% are saving money) by assessing short-term saving practices and putting off buying homes and starting families (Morris & Hedges, 2024;

Merriman et al., 2022). They prefer to spend money on experiences like travel or dining with friends that create memories and connections as an essential piece of success rather than buying things (Merriman et al., 2022). Spohn (2017) found that Gen Z has a fear of missing out on anything, more so than previous generations, which may contribute to their desire to travel and create memories.

Reaching Gen Z

Social media marketing provides universities, colleges, and employers opportunities to access, engage, and build relationships with prospective candidates (Clark et al., 2017; Mwenda et al., 2019; Pham et al., 2020; Levesque, 2022). Bergamo et al. (2012) stress that "relationship marketing is critical to create and maintain a relationship between institutions, students or employees; such relationships are being developed towards customer/employee retention and loyalty" (p.26). Unlike traditional means of communication, television and print media, social media provides flexible, low-cost, two-way communication (Pham et al., 2020). HTML-embedded coding allows video sharing on multiple media platforms (Pham et al., 2020). So, although YouTube may be the current social media preference, Threads, TikTok, or X may be the Gen Z platform choice for tomorrow. In addition, organizations on social media receive feedback on messaging and content on a like or dislike basis and gather data by enabling and monitoring the comment section.

Levesque (2022) found that Gen Z uses the internet as their primary tool for researching potential universities, community colleges, and employers. Therefore, institutional websites should be user-friendly, easy to navigate, and provide the information candidates seek, like tuition, financial aid options, accurate program and job descriptions, graduation and acceptance rates, job placement, and information about campus tours (Levesque, 2022). Visually appealing homepages that focus on the student experience in a particular major and discuss internships, job opportunities, and social engagements may pull students into higher education enrollment or employment (Levesque, 2022).

Recruiting Gen Z

Persuasion requires transmitting a message consisting of arguments or simple cues, like music in messages that evoke specific responses in the receiver (Petty & Cacioppo, 1986). Mwenda et al. (2019) and Pham et al.

(2020) found that message and content style mattered when attempting to persuade potential Gen Z recruits. Mwenda et al. (2019) examined discipline-specific YouTube videos for recruiting Gen Z for STEM-related career choices. This study found the video content they analyzed to be homogenous and failed to differentiate one program from another and one university from the next. At the same time, the Pham et al. (2020) study focused on a review of educational institutions' video YouTube messaging and found that "in general, universities adopt a quasi-standardized 'recipe' in both information content and appeal messages" (p. 92). The Mwenda et al. (2019) and Pham et al. (2020) studies tell the story of missed opportunities to introduce recruits to the uniqueness of each program and institution. Furthermore, videos tended to focus on pulling potential recruits who had already decided to attend a four-year university to their institution rather than trying to push undecided candidates toward deciding to attend college.

Prospective candidates seek personal engagement with institutions but not necessarily in-person contact (Dejarnette, 2019). Organizations increasingly realize it is not enough to attend a college or job fair because they compete for a dwindling number of candidates (Dejarnette, 2019). Universities and employers must meet recruits with an authentic and credible message on a large scale via digital and social media (Dejarnette, 2019).

Certifications and Alternative Credentials

As Gen Z turns away from college degrees, they increasingly seek certifications and alternative credentialing, sometimes referred to as alt creds, to grow skills and offer 'proof' of knowledge (Westfall, 2023). With over a million forms of alt creds, including certifications awarded by U.S. organizations, it is increasingly difficult to distinguish good, bad, or fake alt creds (Westfall, 2023). Additionally, employers are moving toward no longer requiring job applicants to have a college degree due to a steep drop in candidates with a bachelor's or an associate degree (Kawamoto, 2023). Yet, for the moment, except for IT and customer service positions, recruiters still rank a college degree as the most valuable credential for most roles (Westfall, 2023).

Many community colleges and regional universities are jumping into the alt creds market. Often marketed as 'Alternative Pathways,' alt creds may entice those members of the Gen Z cohort still in high school to enroll

in alternative credentialing programs, in addition to capturing those disengaged Gen Z learners who may have started at a university but dropped out prior to completing a degree program. A recent study of disengaged learners conducted by Straighterline and the University Professional and Continuing Education Association (UPCEA) found that those with some college, no credential (SCNC) are looking for institutions to provide credit for prior learning (Straighterline & UPCEA, 2023). Although this study found that the SCNC Gen Z population continues to grow and re-engagement rates are still declining, offering online self-paced programs and prior learning assessments to provide credits for demonstrated knowledge and skills may offer a path for degree/program completion (Straighterline & UPCEA, 2023).

The Negative Implications of a Generation without a Higher Education

The failure to reach and recruit Gen Z and push high school graduates toward higher education is already being felt in the private sector. Recently, a Taiwanese semiconductor manufacturer planning to start production at a U.S. facility was forced to postpone due to a shortage of skilled labor (King, 2023). The Chips and Science Act of 2022 set aside billions of dollars to boost the industry domestically, creating 460,000 new positions; however, based on current trends, 67,000 jobs will go unfilled unless something changes (King, 2023).

The U.S. manufacturing industry is on the verge of a comeback due to supply chain weaknesses and the over-dependence on overseas suppliers that were exposed during the pandemic (Fried, 2022). Furthermore, a recent Deloitte study of the U.S. manufacturing industry (2021) predicts that 2.1 million jobs will go unfilled due to a skilled workforce shortage by 2030 (Wellener et al., 2021). Primary drivers include Boomer retirements and a loss in interest in manufacturing jobs by Gen Z. Given the large population in the U.S., the country's extensive network of colleges and universities could ensure that many individuals receive a post-secondary education. However, the U.S. in 2021 ranked 13th in the population aged 25-34 with a post-secondary education, with only 51.17% of its population holding tertiary qualifications (Organization for Economic Cooperation and Development, 2022). This shortage of workers may represent a lost opportunity cost of 1 trillion dollars or about \$3,100 per person in the U.S. per year (Wellener et al., 2021).

Beyond the potential effects on the U.S. economy, the lifelong impact on Gen Z could be devastating. Carnevale et al. (2023) found that individuals who opt out of a college education tend to make 75 percent less over a lifetime than cohort members with a bachelor's degree. The U.S. Bureau for Labor Statistics (2022) reported that the unemployment rate for individuals with only a high school diploma (4%) was double that of a college graduate with a bachelor's degree (2%). Additionally, a study by The Center for Divorce Education (2023) found that higher education levels are associated with lower divorce rates. Individuals with a high school diploma have a rate of 38.8%, whereas those with a bachelor's degree have a divorce rate of 25.9%. This study implies that the factors contributing to the correlation between divorce and education are economic stability, cognitive and social skills, the ability to communicate effectively, and informed decision-making, all of which are skills and abilities gained through post-secondary education.

Discussion

As of 2023, about half of Gen Z's U.S. population is still in high school, junior high, and elementary school, so as discussed earlier, there is still time to address this trend. Gen Z clearly stated they felt their K-12 education has not, and is not, preparing them for life after high school (Della Vollpe, 2022; Willcoxon & Marken, 2023). Further, Gen Z has clarified that they want an educational approach directly tied to a career, without college debt, and benefiting or, at least, not harming the environment. Nevertheless, thousands of STEM-related jobs go unfilled. Additionally, Gen Z has stated that they are concerned about social justice, specifically gun violence and police brutality. However, the International Association of Chief of Police reports that 65% of their members have too few candidates applying for vacancies (Columbia Southern University, 2022). Perhaps it is time for a candid conversation about realistic career paths with students at a younger age.

Regional, community, and technical colleges offer an alternative to a traditional bachelor's degree by providing a shorter, less expensive, direct career path in high-demand industries. Gen Z can find a variety of STEM programs, from Urban Forestry to Construction Management to Manufacturing Technology. They can enroll in programs focused on Criminal Justice and Emergency Services; the best way to address concerns about police brutality and gun violence is to be part of the solution. Regional,

community, and technical colleges also offer a variety of accredited certifications, skilled trades apprenticeships, and water/wastewater operator licensing programs. Apprenticeship and licensing classes can be paired with a workforce development program, permitting students to gain the necessary experience to pass required testing. Licensed candidates, especially those with an associate or bachelor's degree, often receive multiple job offers.

Many regional, community, and technical colleges have 2 + 2 or pathway programs that act as transfer portals, where Gen Z can earn course credits toward a four-year bachelor's degree at more affordable prices. Additionally, as Gen Z ages and decides success may be more than traveling and having dinner with friends, community colleges have classes in business management for Gen Z who may want to move into a leadership position and entrepreneurial technology courses designed for individuals who wish to start and own a business.

Finally, research tells us (Duffet, 2020; Armawan et al., 2023; Thomas, 2024) that Gen Z relies heavily on the internet for news and information, particularly on YouTube. A quick YouTube search reveals that many universities are not adopting Gen Z internet recruitment strategies. Gen Z tends to watch a short video and then deep dive if interested; however, the promotional videos offered by prominent universities and colleges tended to be two to ten years old and lacked information. Although short, they followed the same grand production formula: dramatic music, play-action shots of young people on campus, and a few scenes of lectures, ending with a narrator reading the university's tagline.

Blake and Weissman (2023) found that regional, community, and technical colleges were the only higher educational sectors to experience growth (increased enrollment) in 2023, and they attribute this growth to industry-specific programming and recruiting. Many smaller, more regional universities and community colleges' promotional videos focus on career paths and academic programs meant to push Gen Z toward education to career, rather than focusing on the 'you will have a successful career because you attended this prestigious university' philosophy.

Conclusion

Like many industries, higher education appears to have tripped, stumbled, and is falling post-pandemic, but there is still time to right itself. The pandemic hit every generation hard, but especially Gen Z. Many Gen Z

in the emerging adulthood phase, forced into remote learning, began to question the value of higher education. Therefore, it is incumbent upon colleges and universities to know and understand what Gen Z values and grasp how to reach this pivotal cohort.

Regional campuses could significantly improve recruitment by increasing search engine-optimized recruiting on Gen Z's preferred platforms, with information on academic programs directly related to career paths, salary information, and employment prospects designed to push Gen Z toward a college education. Additionally, regional campuses of four-year institutions may benefit from establishing flexible programs with local technical and community colleges that allow Gen Z to begin their educational journey without crippling debt. Finally, a skilled labor shortage will have a devastating effect on the U.S. economy when manufacturing is making a comeback in the United States, as well as the potential loss of earned income Gen Z may face due to a lack of education. There is still time to reach Gen Z, but action is required now.

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Machine Learning for Paleontology Education: Two Outside the Classroom Case Studies

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Machine learning is rapidly revolutionizing the biological sciences and the geosciences. It has the potential to advance paleontology education by providing students with hands-on experience in data analysis and problem-solving. This study explores the application of machine learning techniques in two case studies: one using random forests to infer morphological measurements from fossils and another using computer vision to classify mammal skulls. The students involved in these projects demonstrated the value of hands-on, project-based learning to understand how modern computer science research techniques can be applied to questions about the fossil record. Both students successfully navigated technical challenges, acquired new skills, and gained confidence in their ability to solve problems outside of the scope of traditional classroom learning. While the models developed in these case studies are modest in scope, they serve as valuable foundational projects for students to explore paleontological research questions. These experiences provide a solid understanding of machine learning concepts and techniques, which can be applied to more complex research questions in the future. By integrating machine learning projects into educational curricula, we can enhance the preparedness of students for careers in paleontology and data science, while also contributing to the broader research enterprise.

Introduction

The fossil record serves as a window into Earth's past, lending important historical context for understanding modern Earth systems. Although it is inherently incomplete and biased, the fossil record can serve as a reliable model for reconstructing past ecosystems and forecasting future patterns (Abdelhady et al., 2024; Alroy, 2001, 2003). In recent years, the emergence of digital repositories with vast datasets has spurred a methodological revolution in paleontology (Abdelhady et al., 2024; Yu et al., 2024). Many of these techniques transcend paleontology and are truly interdisciplinary, with origins as widely distributed as physics (Puttonen et al., 2018), medicine (Padian et al., 2004), and statistics (Langley, 2011).

Beyond paleontology, machine learning is revolutionizing research efforts in the biological sciences and geosciences. Machine learning is a technique where a computer is taught to learn like humans, typically through a combination of statistics and artificial intelligence (AI). The core concept behind machine learning is that the machine is constantly learning and improving from new input data. Typically, researchers produce a model using training data, and then apply the model to forecast patterns on test data (Langley, 2011). Unlike traditional statistics, machine learning algorithms typically do not identify association between variables (Mohri, 2018). Machine learning techniques have been applied broadly in the biological sciences and geosciences in recent years (Dramschi, 2020; Ghosh & Dasgupta, 2022; Karpatne et al., 2018; Lary et al., 2016; Vanaja & Yella, 2022). Here, we will focus on two methods of machine learning: random forests and computer vision. Specifically, we will explore two case studies using machine learning as an educational tool for teaching paleontology in outside-the-classroom settings.

Computer vision is a type of artificial intelligence that aims to train computers to identify, interpret, and analyze visual data, typically in the form of photographs or videos (Szeliski, 2022). Traditionally, paleontology has relied on manual methods for identifying, classifying, and interpreting fossils. Although this process is foundational for training paleontologists, it is susceptible to human error and inherently subjective. Computer vision models have been successfully trained to recognize, categorize, and analyze fossils with efficacy comparable to that of human experts (De Baets, 2021; Ferreira-Chacua & Koeshidayatullah, 2023; Liu et al., 2023). Unlike human methods, computer vision models are inherently reproducible and scalable, making them more accessible beyond just the subject matter experts.

Random forests, sometimes called random decision forests, are popular machine learning algorithms that make predictions and classifications using a series of decision trees (Parmar et al., 2019). Random forests excel at classifying subsets of large datasets to create regression models for predictive analytics (Parmar et al., 2019; Pranckevičius & Marcinkevičius, 2017; Svetnik et al., 2003). Because they excel at classification and prediction, random forests can be readily applied to fossils (Abdelhady et al., 2024; Yu et al., 2024). Given sufficiently large datasets, random forests can be used to develop models that can predict missing values for fragmentary datasets, such as the fossil record.

Here, we examine the machine learning as a tool for teaching paleontology in non-traditional, outside-the-classroom settings. We present two case studies of individualized learning through machine learning projects. The first was a summer Research Experience for Undergraduates (REU) at Miami University. The student (ZIM) created several random forest models to infer morphological measurements from fragmentary fossils. The second of these was an advanced high school research experience conducted through Ivy Mind Consulting. The student (MY) created a computer vision model to identify and classify mammal skulls into taxonomic bins. Both students were supervised by the lead author (CMP). Here, we discuss each case study and draw conclusions about the efficacy of machine learning as an educational tool for outside-the-classroom research experiences in higher education.

CASE STUDY 1

Objectives

The fossil record is inherently incomplete. Machine learning models excel at classification and prediction, even when datasets are sparse or fragmentary (Abdelhady et al., 2024; Yu et al., 2024). Traditional regression models often require large datasets, but random forest decision trees are increasingly able to uncover patterns and make predictions even when datasets are incomplete (Hapfelmeier & Ulm, 2014; Loh et al., 2019). Although the research questions vary across these studies, the end goal is the same: to uncover patterns from partial datasets that can be used to infer potential information about missing data.

Geometric morphometric analyses typically rely on several morphological measurements to compare across a study sample (Zelditch et al., 2012). However, this methodology is limited by the fact that most fossils

are incomplete. Fossils are often broken or otherwise damaged by taphonomy and diagenesis (Behrensmeyer, 1978; Behrensmeyer et al., 2000; Behrensmeyer & Miller, 2012). The goal of the project in this case study was to train a random forest model using decision trees to accurately infer missing data from fossil and modern specimens. A secondary goal of the project was to develop a web application that could be operated from a mobile phone. This would make it convenient for a researcher in a museum collection to enter known measurements from a specimen and quickly predict values for missing measurements.

The project in this case study was structured to maximize the student's learning experience. This project required the student to engage in both front-end and back-end development. As a result, the student oversaw the project through the complete lifecycle, from conception to implementation.

Methods

The dataset for this case study, which consists of photographs of fossil and modern whale mandibles, was sourced by the second author (RJS). This dataset was initially sourced for a separate research project, but repurposed for this case study. The REU student digitally measured nine morphological measurements using ImageJ (Table 1). The final morphometric dataset included 63 complete specimens with all nine measurements, and 139 fragmentary specimens with only some values. This dataset spanned 124 extant and extinct whale species.

Table 1: List of measurements used in Case Study 1, with precise anatomical definitions and the view from which they were measured.

Value	Definition	View
SL	Straight anteroposterior length from rostral tip to articular process	Lateral
SY	Anteroposterior length of the mandibular symphysis	Dorsal
M1	Posterior margin of the articular process to tip of the coronoid process	Lateral
M2	Posterior margin of the articular process to posteriormost tooth	Lateral
M3	Posterior margin of the articular process to posterior end of the symphysis	Dorsal
M4	Broadest transverse width across the articular process	Dorsal

M5	Anterior tip of the rostrum to center of the 3 rd tooth (if present)	Dorsal
M6	Transverse width of the mandible at the level of the 3 rd tooth	Dorsal
M7	Transverse width of the mandible at the posterior end of the symphysis	Dorsal

The student initially coded the random forest model using decision trees in a local environment using Python. This approach allowed for fast iteration and provided an opportunity to learn troubleshooting in a local setting. For preliminary data exploration and visualization, the student utilized the Seaborn library. They then executed the random forest model using the SciKit-Learn library. SciKit-Learn is an open source data analysis library that is beginner friendly and commonly used for teaching entry level machine learning concepts.

Once the model was refined, the student moved to the online platform Kaggle. Kaggle is an online community platform for data science competitions which offers notebooks for coding in Python in a virtual environment. In the Kaggle environment, the student fine-tuned the model for increasingly precise binary splits, optimizing for lower mean absolute error values. Code for the final model is available as supplementary files in the Appendix.

Results

To evaluate the accuracy of the model, the student retained measurements from 30 complete whale mandibles that were not included in the training dataset. This dataset was equally distributed among taxonomic groups. The random forest model was optimized for the lowest possible mean absolute error (a measure of error between the predicted values and the actual values in the test dataset for each variable). The model was able to accurately predict linear measurements with a mean margin of error of approximately 5% of the estimated value.

Additionally, the student added code to assign an importance score to each of the nine variables. This score indicates the contribution of each variable to successfully predicting the other eight. The results indicate that M7, M3, and SL collectively comprise nearly 90% of the model's predictive power. This suggests that the other six variables are of limited utility as proxies for missing data and may not be worth collecting in future studies.

Once the model was finalized, the student built a web application for users to interact with it. The application was built and hosted on the web platform HuggingFace: an open source platform for hosting and testing generative AI models. The web application built by the student is mobile friendly for convenient use in museum collections. The user inputs given morphological measurements taken from a physical specimen and then receives as an output a prediction of the missing values, as well as a margin of error. The web application was built primarily in Python, with minimal coding in JavaScript to design the user interface.

CASE STUDY 2

Objectives

Some of the earliest attempts to use machine learning for paleontological research involve the identification and analysis of images (Liu et al., 2023; Puttonen et al., 2018). The specific objectives vary from analyzing morphology to taxonomic classification, and the images in question range from photographs or videos to SEM or CT scans. However, the end goal is the same: to train a computer to recognize paleontological images with near-human accuracy so that the process can be automated (Szeliski, 2022; Yu et al., 2024).

Although taxonomic identification is crucial for research purposes, it is also critical for curation and management of voucher specimens in research repositories. The goal of the project in this case study was to train a computer vision model that could reliably categorize photographs of mammal skulls into their respective mammalian Order. A secondary goal of the project was to develop a web application that could be operated from a mobile phone, making identification and curation of skulls quick and convenient without sophisticated software.

As in the first case study, this project was designed to maximize the student's learning experience. The project required the student to engage in both front-end and back-end development. This structure ensured that the student oversaw the project through the complete lifecycle, from conception to implementation.

Methods

The dataset for this case study was sourced by the lead author and PI (CMP). It is comprised of photographs of mammal skulls from the Smithsonian National Museum of Natural History (USNM), University of

Michigan Museum of Zoology (UMMZ), and the Hefner Museum of Natural History (MU). The full dataset included 738 artiodactyls, 1134 terrestrial carnivorans, 240 bats, 166 lagomorphs, 2006 pinnipeds, and 671 rodents. The photographs include a range of different views (dorsal, ventral, lateral, and oblique) and further differ in the presence or absence of the mandible. These differences were preserved to mimic real conditions under which a user may attempt to use the model.

The student initially created a prototype model in a local environment with Python using only a subset of the data set. Working in a local environment allowed for faster iteration and provided valuable troubleshooting experience for the student. The student built this prototype using the fast.ai library with ResNet18 as the base model. The ResNet models are deep learning image recognition models of varying complexity; ResNet18 is a low-resource model that is ideal for fast iteration of preliminary code.

Once the prototype model was operational and ready to scale up to the full dataset, the student moved to the online platform Kaggle. Among its many features are notebooks for coding in Python in a virtual environment, which use machines hosted by Kaggle. These machines had faster GPUs that could more efficiently process both the complete dataset and a more complex ResNet base model. Code for the final model, which uses ResNet152 as its base, is available as supplementary files in the Appendix.

Results

To evaluate the accuracy of the model, we retained 60 photographs of mammal skulls that were not included in the training dataset. This test dataset was equally distributed across the six orders included in the training dataset. The final model trained on the ResNet152 base correctly assigned all 60 photographs to the appropriate order, and never dipped below 90% certainty. These scores are comparable to human experts, and more than sufficient for both research and curatorial purposes.

Once the model was fully trained and tested, the student built a web application with a minimal user interface for interacting with the model. This web application was built and hosted on the platform HuggingFace. This web application is mobile phone compatible, allowing for easy access to a camera. The user inputs a photograph of a skull and receives a prediction of the mammalian order to which the skull belongs.

The web application was built primarily in Python, with minimal code in JavaScript to design the user interface.

Discussion

In this study, we examine the application of machine learning techniques as teaching tools for teaching paleontology in outside-the-classroom settings. We present two distinct case studies—one focusing on random forests for inferring morphological measurements, and the other on computer vision for classifying mammal skulls. Our case studies demonstrate the value of hands-on, project-based educational experiences for students interested in paleontology. Here, we examine the educational outcomes derived from these projects, highlighting how hands-on engagement with machine learning can foster a deeper understanding of the subject matter and develop key coding and research skills in junior researchers. By comparing the two case studies, we draw broader conclusions about the role of machine learning in science education.

The first case study was executed by a summer REU student (ZIM) at Miami University. The student acquired technical skills in Python and gained a strong understanding of how random forests operate, particularly in the context of handling incomplete datasets. The student faced several important challenges, such as troubleshooting errors during model development and refining the model for accuracy. Overcoming these challenges was a critical part of developing the student's problem solving abilities for future research endeavors. By designing a prototype web application, the student was able to successfully see a project through from conception to implementation. In addition to its value as a research experience, this work serves as a critical portfolio piece for students interested in data science, software development, or project management careers.

The second case study was conducted by a high school student (MY) through an advanced research program at Ivy Mind Consulting. During this project, the student developed technical proficiency in Python and gained a deep understanding of computer vision techniques, specifically using the fast.ai library. The student encountered and overcame challenges related to training and scaling deep learning models, which significantly contributed to their ability to troubleshoot and optimize complex algorithms. By building a prototype model and eventually scaling it to handle a full dataset, the student demonstrated strong project management skills and the ability to

iteratively improve their work. The final product, a web application for mammal skull classification, not only served as a capstone to their learning experience but also provided a tangible asset for their portfolio. This research experience is invaluable for a researcher at such a junior stage, as their career trajectory is still undefined. The capstone product resulting from this project will be instrumental in securing a future in data science, machine learning, or software engineering.

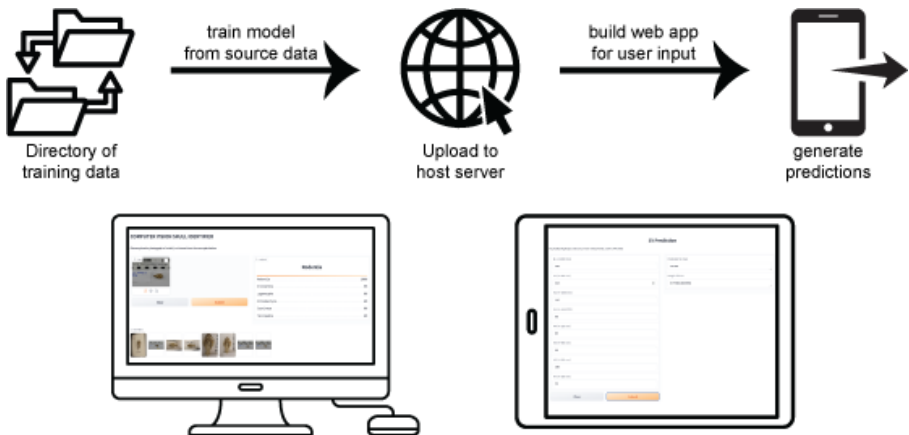


Figure 1: Generalized procedure for both machine learning case studies. Each project began with a directory of training data, which was used to train the model, and was then uploaded to a host server (www.kaggle.com). Once the model was trained, the student built a web application with a user interface and hosted the web application on an online platform (www.huggingface.com). The end result were simple web applications that users can provide an input to in order to query the model for predictions.

Parallels across both case studies highlight the value of key educational objectives (Figure 1). Both students developed foundational skills in Python and gained hands on experience with advanced machine learning techniques. Both students initially built prototype models in local environments where they could iterate quickly. Similarly, both students faced challenges in scaling up the model to full datasets and subsequently optimizing the model for minimal error. By designing both case studies with similar approaches, the students were able to benefit from discussing their projects with one another and helping each other problem solve. Both students successfully managed their project from conception to

implementation, resulting in tangible products for them to use as resume and portfolio pieces.

Both students self-reported high levels of satisfaction with their learning experience. Despite having limited prior exposure to Python and AI projects, they were able to successfully overcome technical challenges. Both students emphasized the importance of the mentorship role for answering technical questions, providing foundational reading, and encouragement. Both students reported elevated levels of confidence in their capability to handle complex, technical, projects and their capacity to problem solve through challenges.

These case studies underscore the broader implications of integrating machine learning into paleontology education. By engaging in hands-on, project-based learning, students not only develop technical skills but also gain confidence in applying these skills to real-world problems. The iterative nature of the projects, from prototype development to full-scale implementation, mirrors the workflow of professional research, providing students with a realistic understanding of the scientific process. Moreover, the collaborative element—where the students discussed challenges and solutions with each other—highlights the importance of peer learning in scientific education. These experiences suggest that integrating machine learning projects into educational curricula can significantly enhance the preparedness of students for careers in paleontology and more broadly in data science, software development, and experimental design.

Our results underscore the effectiveness of machine learning as a teaching tool in paleontology, particularly in non-traditional, outside the classroom settings. Both students successfully navigated the complexities of their research projects, from initial concept to product launch. Both students successfully built prototype models that could serve as the foundation for more sophisticated, research-applicable models in the future. In doing so, both students gained valuable professional development for their early career stage. As the field of paleontology continues to evolve, incorporating technological approaches into educational practices will be crucial for preparing the next generation of researchers. Future initiatives should continue to explore and expand the role of machine learning in both formal and informal educational settings.

Finally, we would like to acknowledge the capacity by these early researchers to contribute broadly to the research enterprise. The models developed in these case studies are simple in scope and ambition, and do

not directly address research questions. Nevertheless, they can serve as foundational projects to inspire and guide future research endeavors. Engaging early career scientists in these types of projects will build a foundation of project ideas and solutions that can inspire research-quality projects down the line. In this way, even early career scientists can contribute to the broader research enterprise.

Author Contributions

CMP and RJS conceived and executed the project. They designed both case studies, prepared, wrote, and revised the manuscript. ZIM conducted the case study 1: building the random forest model to infer missing data. MY performed case study 2: building the computer vision model to categorize skulls. CMP supervised, mentored, and assisted both students with their projects.

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Improving Undergraduate Students' Chemistry Self-Efficacy Through Metacognitive Training

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Self-efficacy is a concept originally developed in the field of psychology and is defined as one's belief that they can complete a certain task or goal. In education, self-efficacy is one affective characteristic that students have that can affect their success in the classroom, so teachers need to be aware of it to help students persevere through STEM courses. Interventions to affect students' self-efficacy have been attempted in the literature, many showing an increase in students' chemistry self-efficacy, including metacognitive student skills training. Therefore, this research paper addresses if metacognitive tutoring sessions affect students' chemistry self-efficacy. Tutoring sessions that covered metacognitive study strategies were implemented with eleven organic chemistry two students at a community college. Students who participated in the intervention had more increased chemistry self-efficacy after the intervention than those who did not participate, based on pre/post surveys and qualitative interviews. By teaching students study skills based in metacognition, chemistry educators can better help their students to be confident with the material, hopefully leading to higher performance in chemistry courses and a stronger retention of students in chemistry courses and STEM careers.

Self-efficacy is a concept established by Bandura (1977) as part of his social cognitive theory. Self-efficacy is a belief that oneself can achieve a specific outcome or objective (Bandura, 1977). This affective characteristic is domain-specific; academic self-efficacy does not apply to all classes, and high chemistry self-efficacy does not mean someone will have high physics self-efficacy, for example (Bandura 1977; Moreno, 2021). Since a student's self-efficacy is a measure of how well a student thinks they will be able to complete certain tasks, researchers have hypothesized and shown that students who have a higher self-efficacy perform at a higher academic level (Bandura 1981).

The connection between self-efficacy and academic performance makes understanding students' self-efficacy a critical area of study in higher

education. Understanding students' self-efficacy allows instructors to gauge students' confidence with chemistry topics and how well they will perform. For STEM courses, which are often quite challenging and can cause many students not to pursue a STEM career, understanding students' STEM self-efficacy can help instructors gauge whether students will persevere with STEM. In undergraduate chemistry classrooms specifically, multiple researchers have found that high academic performance in chemistry is correlated with high self-efficacy scores (Moreno, 2021; Ramnarain & Ramila, 2018; Wilson-Conrad 2018). Given the correlations between academic performance and self-efficacy, multiple researchers have studied interventions in chemistry classrooms and labs to impact students' self-efficacy and performance through problem-based learning (Mataka & Kowalske, 2015), flipped classrooms (Naibert et. al. 2021), and metacognitive training (Gamby and Bauer, 2022; Graham et. al. 2019). This research indicates that there is a connection between students' chemistry self-efficacy and academic performance as found through quantitative means. Therefore, there is a need for more qualitative research to better understand the connection between academic performance, student understanding, and chemistry self-efficacy with undergraduate chemistry courses and diverse undergraduate students.

The research question this study aims to address is how metacognitive tutoring sessions affect students' chemistry self-efficacy? The literature review presents the research in self-efficacy in chemistry higher education and what interventions have been used to affect it. The methods section describes the design of the intervention and its participants. The results and findings section discusses both the results of the pre/post self-efficacy survey as well as excerpts and findings from the student interviews. The implication and conclusion sections summarize the findings and provide educators from all disciplines ways they can utilize the findings in this study.

Review of Literature

The literature review is divided into two main sections. First, the connection between self-efficacy and academic performance that researchers have established in specific contexts is explored. Then the interventions that science education researchers have used to affect students' self-efficacy will be presented.

Self-Efficacy and Academic Performance

Bandura's original review of his self-efficacy research was with psychology patients with phobias (Bandura, 1977). His research showed that patients' self-efficacy predicted their performance on tasks better than past performance did. Bandura found self-efficacy information came from four different sources: mastery experience, vicarious experience, verbal persuasion, and physiological reaction. Mastery experience refers to a person successfully completing a task in the past, which can increase their self-efficacy related to that task. Vicarious experience is seeing other people successfully complete the desired task, which encourages the person that they can also succeed if they are persistent. Verbal or social persuasion is convincing someone through social interactions they can achieve a task. Finally, physiological reactions are the ways in which people respond to a given situation; increased anxiety will make a person more likely to think they are incapable of succeeding with a task. Of all four sources, Bandura found mastery experience to be the main source of patients' self-efficacy (Bandura, 1977).

Research into self-efficacy in college science classrooms has been both quantitative and qualitative (Flaherty, 2020). Quantitative scales measuring self-efficacy have been created for different types of general and organic chemistry college classrooms. Using these scales and other means, researchers have explored the connection between students' self-efficacy scores and their exam performance (Villafañe et. al., 2016; Willson-Conrad & Kowalske, 2018). Both Villafañe et. al. (2016) and Willson-Conrad & Kowalske (2018) investigated performance on exams as compared to students' self-efficacy, and the researchers found students with higher self-efficacy generally performed better on chemistry exams and had lower test anxiety. Willson-Conrad & Kowalske (2018) found, via interviews, their highest performing students in general chemistry exams had high chemistry self-efficacy due to mastery experiences (i.e. previous success with chemistry content) while middle performing students obtained self-efficacy beliefs from vicarious experience (i.e. comparing their exam scores to their peers to evaluate their perceived ability). Villafañe et. al., (2016) found pre-exam organic chemistry self-efficacy scores predicted students' exam performance, and exam performance had positive effects on self-efficacy, indicating that mastery experience is a major source of students' self-efficacy.

Other studies found chemistry self-efficacy could be correlated to overall academic performance. The College Chemistry Self-Efficacy Scale has been used in chemistry higher education in both the United States (Ferrell et. al., 2015) and South Africa (Ramnarain & Ramila 2018) and has been found to be a reliable way to predict students' chemistry self-efficacy. Using this scale, these same groups have also found that self-efficacy was able to predict students' final course grade (Ferrell et. al., 2016) or final cumulative exam score (Ramnarain & Ramila 2018). Chan and Bauer (2014) have also confirmed that students with high self-efficacy (as measured by examining students' motivation) tend to perform better in their college chemistry courses. When Moreno et. al. (2021) looked at multiple factors (i.e., gender, SATM score) to predict students' course GPA in introductory and general chemistry courses, they found post-test chemistry self-efficacy scores best predicted GPA. These studies are examples that, according to pre- and post-course data from chemistry self-efficacy scales, students with higher self-efficacy perform better in chemistry courses than students with lower self-efficacy.

While the above studies show a clear connection between self-efficacy and academic performance, there are other factors to consider. First, the positive correlation between performance and self-efficacy has not always meant that self-efficacy increases linearly (Villafañe et. al., 2016). Average self-efficacy scores in this study fluctuated throughout the semester, which meant students' self-efficacy did not only increase with further chemistry instruction. However, this trend would not be possible to observe in other cases, as most researchers only assessed self-efficacy at the beginning and end of the course, which does not allow students' self-efficacy across a semester to be evaluated (Villafañe et. al., 2016). Second, self-efficacy has not always been found to be the best predictor of course performance. Gibbons & Raker (2019) found that self-concept, not self-efficacy, was the best predictor of exam performance. While not in a chemistry context, McBride et. al. (2020) evaluated non-science majors' science self-efficacy at a liberal arts college and found their science self-efficacy was not the best predictor of their academic performance. These examples point out the exact connection between chemistry self-efficacy, academic performance, and student understanding is still not entirely understood. Therefore, research on self-efficacy, particularly in tutoring settings, may provide a valuable contribution to understanding the link

between the effects that chemistry self-efficacy has on academic performance and vice versa.

Interventions that Affect Self-Efficacy and Metacognition

There have been both classroom- and electronic-based interventions implemented in college science and chemistry courses to determine the effects on students' self-efficacy. Naibert et. al. (2021) found general chemistry one and two students had improved chemistry self-efficacy scores after a semester of flipped classroom instruction. Mataka & Kowlaske (2015) found students who took general chemistry courses with a problem-based learning unit had a higher chemistry self-efficacy after the course, and interviews after general chemistry two revealed the increase was due primarily to the PBL unit. Amelink et. al. (2015) found community college STEM majors who attended a summer research internship in their field of study had improved research self-efficacy from all four sources of self-efficacy, based on students' reflective journal entries. In one specific example, the researchers found the mentoring the students received from the professors and graduate students provided a boost to students' self-efficacy via vicarious experience (Amelink et. al., 2015). These are only a few examples of the interventions that have been implemented, clearly showing that there are a variety of ways to impact students' science self-efficacy.

Another intervention used by multiple groups is metacognitive training. Since metacognition is considered an aspect of self-regulated learning, it makes sense that improving students' metacognition would help them to be successful in achieving their goals of being successful in chemistry (McDowell, 2019). Teaching science students about metacognition has been shown to increase students' success in the courses, as well as their self-efficacy (Graham et. al., 2019). Graham et. al. implemented weekly tutoring sessions as part of a general chemistry course that combined teaching metacognitive skills and ways for students to use those skills in a chemistry context. They found students who received the training scored higher in self-efficacy than those who did not, and the gap in self-efficacy between men and women was eliminated with the training (Graham et. al., 2019). In another example, Gamby & Bauer (2022) implemented an online module in a general chemistry one course at a community college that focused on metacognition, which was found to give students explicit metacognitive knowledge that they implemented in the course and in their life. Finally, Cook et. al. (2013) incorporated a fifty-

minute lecture about metacognition and how it could help students with their general chemistry course. They found students who attended the lecture achieved an entire letter grade higher than their peers who did not attend the lecture. These examples show metacognition is a promising way to promote student self-efficacy and that it has the potential to improve students' course performance as well. Providing metacognitive instruction in a small group setting could be an effective intervention to positively affect students' chemistry self-efficacy.

The research question this study aims to address is: how can teaching students metacognitive skills during tutoring affect community college students' chemistry self-efficacy? Since metacognitive instruction has been found to both increase chemistry self-efficacy (Graham et. al, 2019; Gamby & Bauer, 2022) and chemistry course grade (Cook et. al., 2013), this seems to be a promising route that deserves more exploration into how it affects students' chemistry self-efficacy and academic performance. While there have been a variety of studies related to chemistry self-efficacy, very few have been done with community college students (Amelink et. al., 2015; Gamby & Bauer, 2022). Considering that many URM students attend community colleges, and there is a gap between URM's representation in the general population and in STEM careers, it's important to find ways that can help URM students remain in STEM (Amelink et. al., 2015). There is also a lack of qualitative data about college students' chemistry self-efficacy (Flaherty, 2020), which this study aims to fill by interviewing students to get a more nuanced view of their self-efficacy.

Methods

A mixed-method approach was used to evaluate how metacognitive study skills taught during tutoring sessions would impact students' chemistry self-efficacy. The study took place during the Spring 2023 semester, which runs from Jan through April. A pre/post survey was used to assess students' chemistry self-efficacy before and after the intervention. Through interviews, sources of students' self-efficacy were explored to identify what sources majorly contribute to students' chemistry self-efficacy.

Setting

The setting of this study is University of Cincinnati-Blue Ash, which

offers associate degrees and other degrees in health-related programs. The students who participated in this study were from Dr. G's second semester organic chemistry course (referred to as organic chemistry two in the rest of this work). Dr. G runs a flipped classroom, where students fill in guided notes outside of class and do practice problems in groups during class. Supplemental videos are provided to students after they have completed and turned in the notes for a particular section. Dr. G also emphasized some metacognitive strategies during her organic chemistry one course the previous semester. Organic chemistry two is required for many science majors, including biology, chemistry, and other health science-related majors. All intervention lessons and interviews were conducted outside of the organic chemistry two class time.

Researcher Information

The researcher is a chemistry tutor in the Science Learning Lab at UC-Blue Ash. At the time of the study, the researcher was in her second year of work as a tutor. The center is a drop-in service that is free for all students at the school. The researcher works with students individually or in small groups who come in with questions about class content, homework problems, or lab work. The researcher works with students who have a variety of different nationalities, ethnicities, ages, genders, and majors. She tries to use a variety of strategies to effectively work with this diverse student population.

Participant Information

The participants were recruited by the researcher visiting Dr. G's organic chemistry two class to tell the students about the study and what it would entail. Students had approximately one week to sign up for the study. Additionally, the students learned more about the study by talking to the researcher when they were in the tutoring center. Students were not offered any point or grade incentive for participating in the intervention. Those who did not participate in the intervention were the control group. The participants in the metacognitive lesson intervention were eleven students from Dr. G's organic chemistry two class. Seven identified as women and four identified as men. All except two students reported they came to the tutoring center daily or multiple times per week. All had taken organic chemistry one the previous semester at the same college, three with the same teacher and eight with a different one. The eleven

participants in the control group only completed the pre and post survey and were not given any metacognitive instruction. The control group had ten women and one man, all of whom completed organic chemistry one at the same institution. Only one person regularly visited the tutoring center and six respondents said they had never visited the tutoring center since Fall 2022.

Survey

A pre/post survey was used to measure students' self-efficacy related to organic chemistry (see Appendix Table A1). The questions asked students how confident (1=least confident, 5=most confident) they felt about major topics from organic chemistry one, which they would have to continue to apply in organic chemistry two. These surveys were administered via Socrative, an online quiz platform, during class periods. The teacher offered two points of extra credit on the students' next quiz score to complete each survey. The pre-self-efficacy survey was given on Jan 25, 2023, before all students had committed to the intervention. The post-self-efficacy survey was given after all lessons and interviews had been completed on Feb 22, 2023. For those not in class the day the surveys were provided, they were given the option to complete a paper survey before the next class period.

Intervention-Study Skills Lessons

To answer the research question, metacognitive study skills sessions were taught to 11 community college students taking the second semester of organic chemistry. There were three lessons that each student attended that took place between weeks 3-7 of their Spring 2023 semester. The lessons were 20-30 minutes long, and students participated individually or in groups of 2-5 students, depending on scheduling. The lessons focused on four metacognitive strategies and how students could use them in their organic chemistry two course. The material was drawn from the Learning Scientists blog (Caviglioli et al, n.d.), a website utilized in the Graham et. al. (2019) study. Specifically, students were sent one or two short videos one day before each lesson that they were told to watch prior to the lesson. During the lesson, PowerPoint slides from the Learning Scientists website were used by the researcher to discuss the different metacognitive study strategies. Lesson one covered retrieval practice and spaced practice, lesson 2 covered elaboration with a focus on concept mapping, and lesson 3

covered interleaving. Throughout each PowerPoint, the researcher discussed ways the metacognitive study practices could be used for organic chemistry, and students provided their thoughts about applying them into their study routines. After each presentation, the students completed an exit slip, which involved answering questions or submitting an example of what had been discussed during the lesson. This allowed the researcher to see what the students learned from the lesson and what they saw as important.

Interviews

Two interviews were conducted with the eleven students involved in the intervention. The purpose was to gain more qualitative data from students, as well as to identify common sources of self-efficacy. Ten students participated in interview one, and all eleven students participated in interview two. Each interview was recorded either on the researcher's phone as an audio recording, or over Zoom if the interview was virtual; verbal consent for recording was obtained from each participant before proceeding. Interview one was conducted the week before the students' first organic chemistry test of the semester. Each interview was individual and was 10-20 minutes. Six main questions were asked, as well as follow-up questions based on students' responses. Questions were related to students' study strategies for the upcoming tests, as well as questions about any test related anxiety they might have. Interview two was conducted at least one day following students' final metacognitive lesson. Seven different questions than the first interview were asked related to students' incorporation of the metacognitive study strategies and their feelings after the first test. Again, follow-up questions were asked based on students' initial responses (see Appendix Table A2 for initial questions for pre- and post-interviews).

Results and Findings

Survey Results

Organic chemistry self-efficacy survey data was collected before and after the intervention to determine if the intervention affected the self-efficacy of students in the experimental group. Of the 26 original students in the class, 23 students took the pre-survey, and 24 students took the post-survey. One student dropped out of the class between the pre and post

survey but did not take the initial survey. 22 students who took the pre-survey also took the post survey; the remaining two students who took the post-survey did not take the pre-survey. Therefore, only the data from the 22 students who took both surveys was used in the analysis.

Table 1: *Average change in students' self-efficacy for the experimental and control groups*

Group	Pre survey	Post survey	Average change	Average % change
Control	3.46	3.54	0.08	+2
Experimental	3.66	4.07	0.41	+11
Overall	3.56	3.81	0.25	+7

After students completed both surveys, the average results for the pre and post surveys were calculated for the overall class and for each group of students (control and experimental). The results per student are presented in Table A3, as well as the average change and percent change from pre to post survey. Overall, most students' self-efficacy scores increased from pre to post test. However, five students in the control group had a decreased self-efficacy score. One student in the experimental group had their self-efficacy score decrease slightly while two more in the group had unchanged self-efficacy. Table 1 shows the average increase in self-efficacy score for the control group was 2% while for the experimental group it was 11%. This indicates that, on average, students who participated in the metacognitive study strategies intervention had an increased organic chemistry self-efficacy after the intervention, even more than the control group. Students in the experimental group also had some of the biggest changes in self-efficacy, with one student increasing their score by 29% from pre to post survey. Further qualitative results will be discussed in the sections below to support the findings that students felt more confident in organic chemistry because of the study skills they learned.

Study Skills Lessons

All eleven students in the experimental group completed three metacognitive lessons that covered four specific study strategies: retrieval practice, spaced practice, elaboration, and interleaving. PowerPoint presentations put together by the creators of the Learning Scientists blog

were used by the researcher to share these study strategies with the students (Caviglioli et al., n.d.). Students overall had positive reactions to learning the study skills. They asked questions about how to incorporate these study strategies in organic chemistry specifically, which sparked helpful and productive conversations about specific applications of the strategies.

The exit slips the students were given after the first lesson was to see if and how they thought they might use spaced and retrieval practice in their studying. All students gave various ways they could try incorporating the study strategies, showing they had understood and were interested in strategies discussed during the lesson. During the second lesson students saw an example of a concept map the researcher had created based on an organic chemistry concept. The exit slip after the second lesson required students to create a concept map related to an organic chemistry term they had recently covered, aromaticity. Even though some students had never heard of or created a concept map before, they all attempted to create one for five minutes at the end of this lesson. After working on it, the researcher talked with the student(s) about what they created and what connections they made. Each student had very different ideas about how to connect ideas together. It gave the researcher the chance to see how the students were making connections between ideas and to identify any misconceptions. Multiple students said they found it challenging but would still attempt to make concept maps for other organic chemistry topics. The exit slip after the third lesson asked students how they would use interleaving and if students were planning to use other strategies throughout the semester. Many students expressed interest in using interleaving as a strategy, and all students said they planned to use at least one study strategy for the rest of the semester.

Interviews

Pre exam interviews. The pre-exam interviews were conducted with ten students from the experimental group prior to the first exam (one student couldn't be interviewed due to scheduling conflicts). The purpose of this interview was to ask students how they prepared for chemistry exams and their general feelings toward their exams. An important note is the majority of the students (eight out of eleven) had a different professor for the first semester of organic chemistry than in the second semester. The other professor implemented quests instead of exams, which were shorter

assessments students could take multiple times to pass, and students had only one full length final exam. Therefore, the students who took the class with the other professor did not have much experience preparing for long organic chemistry assessments.

Overall, students reported feeling confident they could be successful on their exam based on their past experience in taking chemistry tests. Even students who had only taken short organic chemistry assessments felt confident they could succeed, due to a mixture of doing well on the quests and doing well on general chemistry exams from prior semesters. When they were asked what study strategies they were using and were going to use to prepare for exam one, many students shared that they were already incorporating spaced practice and retrieval practice from the first lesson. One common way that students were doing this was through flashcards, which had been discussed as a way to both help memorize the products of the reactions without mechanisms and to write down the mechanisms for reactions that had them.

The students were also asked if they liked to work with other students when studying. Many students actively planned to meet with others for a variety of reasons. One reason was to help each other when someone in the group didn't know how to do something. Student 10 described it as if "they [another student] don't know something, I'm able to explain and then I see how well I know the material explaining it to them. And then I'm like, yeah I actually I get it. I got the material because I'm able to explain it to you." Some students described that they liked to work in groups because of the support they felt. Student 6 described the support they could provide each other as "validation that if we both don't know something, it's ok, at least I'm not the only one who is completely lost on this specific topic." Feeling like they aren't alone in not understanding things makes some students feel supported and helps them believe they can work through it together. An important point is that some students said the main way they work with others is in the tutoring center. They wouldn't necessarily make plans to work with other students, but they knew when their classmates would be studying in the tutoring center, so they could end up working together. This is an important note because the only two students who did not like to work with other students at all were students who rarely come to just study in the tutoring center. From the interviews, it seems like part of the reason they don't come to the tutoring center is that they would rather work alone than in groups, so they don't see the need to

be around a lot of people when studying. They both mentioned that barriers to working with others were noise from students working together and wanting to understand things fully before interacting with others.

Students were asked about their past experiences with test anxiety in previous chemistry courses. Many students said they felt anxious about their chemistry tests before, during, and after the test. While some students reported not feeling as anxious last semester when they were taking lower stakes quests, they still expected to feel test anxiety for their upcoming test based on previous chemistry classes. Some students worried that they would not know everything that they would see on the test, so they would get overwhelmed and stuck on problems they didn't know how to do. Others worried about overthinking problems and second guessing themselves, which increased their anxiety. Student 4 describes this, saying "I just get even more anxious because I know the answer, but I'm second guessing myself so that just puts even more pressure on me."

Students also provided ways that they cope with the anxiety. They mentioned taking deep breaths, telling themselves they can do this, and writing on the top of their paper "don't second-guess yourself". Others spoke about going into the exam with a better attitude, so that they will get the desired result. Student 5 reported not feeling much anxiety around tests because of the attitude he had when taking the exam, as he described: "If you go in there thinking you're gonna do good, you'll do good. You go in thinking you're gonna do bad, you're gonna do bad. So go in thinking you're gonna do good." Overall, while most students did feel anxiety about exams, many had methods to prevent it from becoming overwhelming during the exam.

Post-interview interviews. The second interview was conducted after students had completed the three study skills lessons. These interviews were conducted to ask how students felt after the first test and to understand how students' study strategies had changed after learning all of the metacognitive study skills. Most students felt pretty confident that they did well right after the test. The most common comment was students worrying about questions they weren't sure if they completed correctly, so they sought help from other students or tutors after the test to ask if what they did was correct. Once students got their score back, most found that the score matched or almost matched how they felt after the exam. All eleven students personally met with the instructor to seek feedback after the exam; some did so only because they gained two extra credit points on

the test by doing so, while others wanted to understand in more detail what they did wrong. Most students who went for the latter reason thought the opportunity for feedback was very helpful, but the biggest complaint was that they could not keep their test or take exact notes about what they did wrong.

When students were asked if they had started to incorporate the metacognitive strategies into their study routine, most said they had at least tried some of the strategies. Many said the strategies made them feel like they knew more of the material and were confident with it. Student 5 said, "I guess like the things we are learning are actually working. I'm going to keep using them. I'm probably going to keep using them until I graduate to be honest." Even in the short few weeks of the study, he had already found the strategies to be something he would continue to utilize for future classes beyond only chemistry. The most common obstacles to students incorporating the new strategies were time management and the difficulty of changing the study methods they had already established during college. Some students had heard about some of the metacognitive strategies before, by a different name, but most students had no exposure to these strategies prior to the intervention. Some students did not know appropriate ways to study. Student 9 admitted, "I thought that cramming was what you were supposed to do... because that's what everyone does usually." These strategies provided him with more effective ways to learn the material and remember it long term.

Most students reported their anxiety in their organic chemistry class went down after learning the strategies. Some even commented that the two strategies they learned the week before the test already helped to alleviate some test anxiety. Student 4 said, "I learned many ways to study, which gave me more confidence on my ability on doing problems on my own, during class and when I'm doing homework and on the exam...I think just having more confidence decreases my anxiety." The study strategies provided her with a variety of ways to practice the material and gave her more confidence, helping to reduce her anxiety. Most said that they didn't let any anxiety they had during the exam affect how they took the test. Others shared that they still struggled with anxiety during the test, due to low self-confidence in their ability to succeed.

The last question students were asked in this interview was if they had any mentors who helped them feel successful in chemistry. A few students said one of their parents was a mentor by believing in them or

helping them with some concepts. Others mentioned the researcher and the other chemistry tutor in the tutoring center were mentors who helped them feel like they could succeed in chemistry. Student 6 described the tutors as people who would “always talk me down after I think that I did really bad. And it never turns out that way.” She also mentioned that having the tutors double-check her work and tell her she was approaching the problem correctly bolstered her confidence. Some students mentioned that previous chemistry teachers were encouraging mentors. Overall, most students had mentors who influenced how they felt about chemistry.

Connections to Sources of Self-Efficacy

Based on students’ first and second interviews, students’ feelings of self-efficacy do not come solely from one source. Some students felt like they could be successful based on their past experiences in chemistry courses, which is an example of mastery experience. It is important to acknowledge that students who did not have experience with organic chemistry tests from the previous semester had less large assessment experiences to draw on, so there were not as many students who said their past experience with chemistry made them more confident as might otherwise have been expected.

Nine of eleven also reported working with other students helped them feel like they could be more successful in organic chemistry. Based on students’ responses, working with others were examples of both vicarious experience and social persuasion; vicarious because students can see other students successfully completing the tasks and social because their peers were providing encouragement to support their success. It is important to note students already had experience working with each other in groups during class time, both last semester and this semester, as both professors utilized the flipped classroom approach. Students’ comments indicate the importance of encouraging students to work together to bolster students’ self-efficacy (in most cases) through watching others complete the task and through encouragement.

The number of times students brought up feeling anxious about assessments or the class as a whole indicates anxiety is an important factor to consider how it affects students’ self-efficacy. Anxiety is one example of a physiological reaction that negatively impacts students’ self-efficacy. Students who let their anxiety impact their exam performance tended to be those with lower self-confidence in their exam taking abilities. Those who

were able to overcome their exam anxiety had established strategies, either physical or mental, that helped them overcome their anxiety to feel more confident in their abilities.

A question about students' chemistry mentors was asked because of findings in STEM research self-efficacy that mentors could be an example of vicarious experience (Amelink et. al, 2015). While this was the question most students had the shortest response to, multiple students reported they had mentors who affected their belief they could be successful in chemistry. Some students even said the tutors at the college campus, including the researcher, had been mentors who gave them confidence that they could be successful. This illustrates the importance of having tutoring centers or other mentors who are not the professors grading the students to bolster students' self-efficacy.

Limitations

This study had some limitations. First, it was done in the span of five weeks. Therefore, it is hard to tell how much students' self-efficacy and study habits really did change in such a short time period and if those study habits would be continued throughout the course. Second, there was a bias in the sample used because most students who joined the study already knew the researcher. Therefore, they were more willing to try the strategies because they had already established a tutor-student relationship with the tutor. Third, the pre/post self-efficacy surveys might not have accurately captured students' true feelings of self-efficacy. Since students were only given surveys at two time points, their responses could have been highly dependent on their feelings or experiences that day. Additionally, the questions on the survey could have impacted students' answers. Students were told to base their answers on their organic chemistry semester one knowledge. This was because putting questions from what students would learn in organic chemistry two on the pre survey would cause an automatic difference between pre and post-test. The questions were also chosen because they were concepts that continued to be used and built upon in organic chemistry two, so it was suspected that students should feel slightly more confident with those concepts by the post-test.

Conclusions and Implications

The results from the study showed that, when students learn and utilize metacognitive study skills, their self-efficacy tends to increase in most

cases, more so than those who did not learn the study skills. Interviews with students revealed that the study skills made them feel more confident with organic chemistry concepts in general and reduced anxiety for assessments. The interviews also revealed that students' feelings of self-efficacy come from a variety of sources, including working with their peers and test anxiety. While other studies have found that mastery experience is usually the main source of self-efficacy for students (Wilson-Conrad & Kowalske, 2018), this study found that many students' confidence and self-efficacy was dependent on their anxiety (physiological reaction). This confirms what one study found, that, based on qualitative data provided by students, their sources of self-efficacy can be more complex (Amelink, 2015). The findings answer the initial research question because it gives insight into how teaching metacognitive study skills affected students' self-efficacy.

This study has implications for those working in higher education in all disciplines. Metacognitive study skills are an important way to help students feel more confident with a subject, as they provide students with effective study strategies that many students are not aware of (Muteti et al., 2021). Professors can promote these skills with their students by spending some time discussing specific study skills with students during class times, especially before assessments, and show them how these strategies can be utilized for that specific course. Professors should also be aware of students' assessment anxiety and ways that they can help alleviate anxiety, so students are not as affected by it when taking assessments. Professors can also encourage students to work in groups, so that the support and encouragement they receive from their peers can increase their confidence. For those working with students in higher education but not in a traditional classroom, being a mentor to students and supportive of their success is very important. Mentoring can positively affect students' self-efficacy if mentors are encouraging and help students to feel confident in their knowledge. Overall, this study provides valuable insights into how metacognitive study skills can affect students' self-efficacy and from what sources college students' self-efficacy arise.

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Appendix

Table A1: *Self-efficacy survey questions. Questions 10-13 were asked on the pre-self-efficacy survey only.*

These questions are based on your knowledge of organic chemistry. On a scale from 1 to 5 (1=least confident, 5=most confident), how confident are you that you can:

1. Recognize a functional group in an organic molecule?	1	2	3	4	5
2. Use the structure of an organic molecule to predict its strength as an acid or base?	1	2	3	4	5
3. Draw organic compounds when given their IUPAC name?	1	2	3	4	5
4. Draw all resonance structures of an organic molecule?	1	2	3	4	5

5. Identify the differences between enantiomers, diastereomers, and constitutional isomers?	1	2	3	4	5
6. Predict the products of organic chemistry reactions?	1	2	3	4	5
7. Draw a mechanism (that you learned) for organic chemistry reactions?	1	2	3	4	5
8. Develop a synthesis when given a starting material and target product?	1	2	3	4	5
9. Determine the mechanism (substitution or elimination) for a given organic reactant and set of reagents?	1	2	3	4	5
10. How do you identify?	Man	Woman	Non binary	Other	Prefer not to say
11. When did you take organic chemistry 1?	Fall 2022	Spring 2022	Fall 2021	Spring 2021	Before 2021
12. Where did you take organic chemistry 1?	At UC Blue Ash	At UC Clermont	At UC main campuses	At a different school	

13. How often have you been to the Science Learning Lab in Walters 200 since the beginning of Fall 2022 semester?	Daily or multiple times a week	Once a week	A few times a month	Once a month	Less than once a month	Never
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Table A2: *Pre-exam and post-intervention interview questions*

Pre-exam interview questions

1. How did you usually prepare for chemistry exams prior to this semester?
2. What study strategies do you plan to use to prepare for this organic chemistry exam?
3. Based on your previous chemistry classes, do you feel confident that you will be successful on this exam?
4. Do you plan to study with others to help prepare for this exam? Why or why not?
5. Do you plan to seek feedback from the teacher about your exam score after the test? Why or why not?
6. Do you get test anxiety before, during, or after taking the test? If so, how does that affect how you take the exam?

Post-intervention interview questions

1. How do you feel like you did on the exam?
2. Did you follow some of the strategies you mentioned in the first interview? If so, what did you use and do you feel like the strategies helped you?
3. Did you have any difficulties in implementing the metacognitive strategies into your study routine? If so, what was difficult?
4. Had you heard of any of these metacognitive strategies before I taught them to you?
5. Do you feel like any test anxiety affected your performance on the exam? If so, how?
6. Do you feel like any of the metacognitive strategies helped to reduce your anxiety level (on the test or subsequent quizzes)? If so, how?
7. How have any mentors, if any, made you feel like you can be successful in chemistry? These could be mentors from before college or during college?

Table A3: *Pre- and post-self-efficacy survey were administered 5 weeks apart.*

Student	Gender	Pre-survey	Post-survey	Difference	Change in self-efficacy (%)
Experimental group					
1	F	4.22	4.67	0.45	11
2	M	4.78	4.67	-0.11	-2
3	F	3.22	3.67	0.45	14
4	F	3.78	4.22	0.44	12
5	M	2.89	3.33	0.44	15
6	F	3.89	4.78	0.89	23
7	F	3.44	4.22	0.78	23
8	F	4.33	4.33	0	0
9	M	3.67	3.67	0	0
10	F	3.33	3.78	0.45	14
11	M	2.67	3.44	0.77	29
Control group					
12	F	3.78	4.33	0.55	15
13	F	2.78	2.89	0.11	4
14	F	3.33	3	-0.33	-10
15	F	3.67	3.33	-0.34	-9
16	F	3.33	3.78	0.45	13
17	F	4.00	4.44	0.44	11
18	F	3.00	3.33	0.33	11
19	F	4.22	4.11	-0.11	-3
20	M	3.89	4.33	0.44	11
21	F	2.89	2.78	-0.11	-4
22	F	3.22	2.67	-0.56	-17

Motivating and Engaging Students in Active Learning Mathematics and AI

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Artificial Intelligence (AI) is math! This paper demonstrates how mathematics works in the development of AI from modeling, training, learning to decision making. A key focus of the paper is to show how AI not only presents a new approach to teaching mathematical applications in the classroom but also serve as a learning tool to solve real world problems. Using mathematical tools, an artificial neural network is built and optimized to predict an individual's gender. The evolving AI tools create active learning environments for students to better absorb abstract mathematical concepts and formulas. They have been proven to be an effective and efficient way to motivate students and keep them engaged, even more so than traditional approaches to higher-level education.

0. Introduction

In the time of ChatGPT, both educators and students are talking about Artificial Intelligence (AI) in and out of classrooms. AI makes predictions via a machine learning process using artificial neural networks, which mimic the brain (Boden 2018). This paper explains the building of a simple neural network from scratch. Terms in neural networks including data mining, machine learning and decision making are introduced with matching mathematical terms. The neural network is designed to predict an individual's gender based on two factors: weight and height. Examples with complete calculation are presented for students to learn more actively and stay more engaged.

While the use of AI within classrooms has been widely debated, it is proven to have positive effects on the learning experiences of students, making it a beneficial and even integral part of education (Wang et al., 2024). After learning derivatives are behind the natural language processing, students show stronger motivation to learn calculus. When using AI, students are enabled to create a model to reduce the pollution of a local lake and they can connect the model to a differential equation. AI helps significantly keep students engaged in learning differential equations. More

importantly, both examples offer hands-on experience for students to handle the major challenges of the world.

1. Function and Neuron

An artificial neural network is composed of interconnected neurons in a layered structure. Mathematically, a neuron is a function which produces outputs based on inputs. A neuron with inputs x_1 and x_2 and one output y is shown in Figure 1.

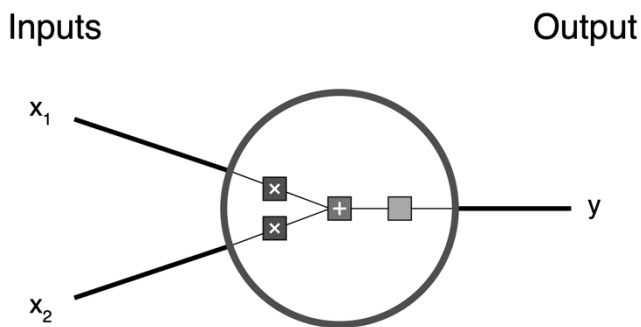


Figure 1. A Neuron

The inputs x_1 and x_2 may inference the output y at different levels. Accordingly, a weight is assigned for each input, w_1 for x_1 and w_2 for x_2 . A model is usually not perfect. There might be missing information from the data collected, or there are hidden features of the model itself. Thus, a new variable b is introduced to provide extra leverage over the model. The variable b is known as a bias in the AI field. Finally, the output y is generated from an activation function with a variable as the sum of weighted inputs x_1 , x_2 and a bias b ,

$$y = f(w_1x_1 + w_2x_2 + b).$$

Note that the weights and the bias can be learned in the machine training process (Aggarwal, 2023).

Every neuron has an activation function. A neuron with a linear activation function is essentially a linear regression model. In most studies, a neuron requires a nonlinear activation function. There are different nonlinear activation functions for different purposes. For example, the logistic function is used for binary classification and the soft-max function is used for multiclass problems. The following logistic function,

$$f(x) = \frac{1}{1+e^{-x}}$$

is used as an activation function for every neuron.

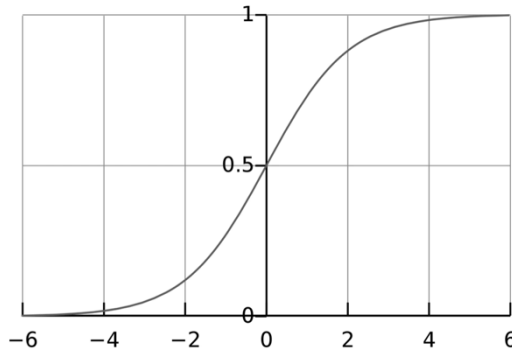


Figure 2. The Logistic/Sigmoid Function

The logistic function is originally derived from the logistic growth model (Stewart, 2010). Its domain is for all real numbers, and its range is $(0, 1)$. It is feasible to generate one binary output from the logistic function. If the function is close enough to 0, the output is assigned 0; if it is close enough to 1, the output is 1. Due to its S shape in the graph shown in Figure 2, the logistic function is considered a sigmoid function. A sigmoid function is a function with an S shaped graph, such as the logistic function and the hyperbolic tangent function, both of which are commonly used activation functions in artificial neural networks.

The process of passing inputs forward to get an output is known as **feedforward** in a neural network. For example, if there is a neuron with two inputs,

$$x_1 = 2 \text{ and } x_2 = 3,$$

with two corresponding weights,

$$w_1 = 1 \text{ and } w_2 = 0,$$

and a bias,

$$b = 4,$$

and a logistic activation function,

$$f(x) = \frac{1}{1+e^{-x}}$$

then the neuron’s output is,

$$\begin{aligned}
 y &= f(w_1x_1 + w_2x_2 + b) \\
 &= f(1(2) + 0(3) + 4) \\
 &= f(6) \\
 &= \frac{1}{1 + e^{-6}} \\
 &= 0.9975.
 \end{aligned}$$

As displayed above, **feedforward** is a mathematical process of evaluating function values.

2. Functional Composition and Neural Network

An artificial neural network is a bunch of interconnected neurons. In the network shown in Figure 3, there are two inputs, one hidden layer with two hidden neurons, h_1 and h_2 ,

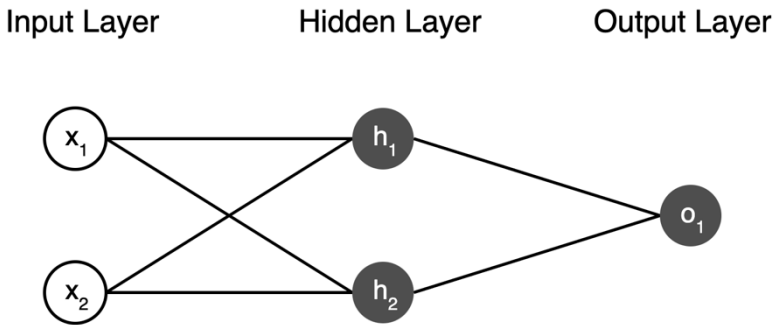


Figure 3. An Artificial Neural Network

and an output layer with one neuron o_1 .

The neuron h_1 has the inputs x_1 and x_2 with corresponding weights w_1, w_2 and a bias b_1 . The neuron h_2 also has the inputs x_1 and x_2 with corresponding weights w_3, w_4 and a bias b_2 . The neuron o_1 has the inputs h_1 and h_2 with corresponding weights w_5, w_6 and a bias b_1 . Indeed, the network is a chain of function compositions,

$$\begin{aligned}
 h_1 &= f_1(w_1x_1 + w_2x_2 + b_1), \\
 h_2 &= f_2(w_3x_1 + w_4x_2 + b_2),
 \end{aligned}$$

and

$$o_1 = f_3(w_5h_1 + w_6h_2 + b_3),$$

where f_1 , f_2 and f_3 are activation functions. Notably, the output is not directly from the inputs x_1 and x_2 , rather from the hidden neurons h_1 and h_2 . Such an arrangement is a typical implementation of an artificial neural network. There can be multiple hidden layers in a network and there can be multiple neurons on each layer. Artificial neural networks are highly efficient because they can solve large scale problems with only two or three layers.

Feedforward in a network is all about function evaluations, certainly a lot more than that of a single neuron. For example, assume there are the following weights,

$$\begin{aligned}w_1 &= w_3 = w_5 = 1, \\w_2 &= w_4 = w_6 = 0,\end{aligned}$$

and the biases,

$$b_1 = 2, b_2 = 1, \text{ and } b_3 = 0.$$

For simplicity, the same logistic activation function is used for all three neurons,

$$f_1 = f_2 = f_3 = f(x) = \frac{1}{1+e^{-x}}.$$

Given the same inputs $x_1 = 2$ and $x_2 = 3$ for a single neuron, one round of **feedforward** is done through the network,

$$\begin{aligned}h_1 &= f(w_1x_1 + w_2x_2 + b_1) \\&= f(1(2) + 0(3) + 2) \\&= f(4) \\&= \frac{1}{1 + e^{-4}} \\&= 0.9820,\end{aligned}$$

$$\begin{aligned}h_2 &= f(w_3x_1 + w_4x_2 + b_2) \\&= f(1(2) + 0(3) + 1) \\&= f(3) \\&= \frac{1}{1 + e^{-3}} \\&= 0.9526,\end{aligned}$$

and

$$\begin{aligned}
 o_1 &= f(w_5h_1 + w_6h_2 + b_3) \\
 &= f(1(0.9820) + 0(0.9526) + 0) \\
 &= f(0.9820) \\
 &= 0.2725.
 \end{aligned}$$

As expected, the output from a neural network is different from a single neuron. AI is built on neural networks. In the examples shown above, weights and biases are randomly chosen. How to choose weights and biases? As a simple answer: no, they are not chosen; however, a machine will learn by itself. Machine learning is the essence of artificial intelligence. It's driven by math!

3. Statistics and Loss Function

Suppose one is presented with a data set on weight, height and gender in Table 1. Can it be discovered how gender corresponds with weight and height? In other words, is there a direct correlation between the two factors?

Name	Weight(lb)	Height(in)	Gender
Adam	152	69	M
Beth	122	63	F
Carol	138	65	F
Dan	148	67	M

Table 1. Weight, Height and Gender

Note in the table, the means are 140 pounds and 66 inches for weight and height respectively. As a standard statistical procedure, the data set is normalized to center around the mean 0 for both weight and height. For gender, male is denoted by 0, female by 1. The normalized data set is shown in Table 2.

Name	Normalized Weight	Normalized Height	Gender 0 male, 1 female
Adam	12	3	0
Beth	-18	-3	1
Carol	-2	-1	1
Dan	8	1	0

Table 2. Normalized Weight, Height and Gender

Now, similar to Figure 3, an artificial neural network can be set up. As a quick review for the network, there is one hidden layer with two hidden neurons, h_1 and h_2 , and an output layer with one neuron o_1 for gender. The neuron h_1 has the inputs x_1 and x_2 with corresponding weights w_1, w_2 and a bias b_1 . The neuron h_2 also has the inputs x_1 and x_2 with corresponding weights w_3, w_4 and a bias b_2 . The neuron o_1 has the inputs h_1 and h_2 with corresponding weights w_5, w_6 and a bias b_1 . The network is a set of functions:

$$\begin{aligned}h_1 &= f_1(w_1x_1 + w_2x_2 + b_1), \\h_2 &= f_2(w_3x_1 + w_4x_2 + b_2),\end{aligned}$$

and

$$y_p = o_1 = f_3(w_5h_1 + w_6h_2 + b_3),$$

where y_p is the predicted gender value, 0 for male or 1 for female. Let y_t denote the true gender value. The input x_1 represents someone's weight, x_2 the height.

The quality of an artificial neural network is calculated with a loss function. The lower the loss, the better the network! There are different loss functions, such as mean squared error, mean absolute error and logarithmic loss. The logarithmic loss is more suitable for binary classification problems. However, for the given example, the mean squared error will be chosen as the loss function. In statistics, the **Mean Squared Error (MSE)** is the mean of the sum of squared errors,

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_t - y_p)^2,$$

where n is the sample size. It is to measure the accuracy of an estimator.

Here is an example on how the loss would be when given a poorly designed network, which will only output the gender value 0 for whatever the inputs are. The following equation is used to calculate this network's MSE,

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_t - y_p)^2$$

$$\begin{aligned}
 &= \frac{1}{4}((0 - 1)^2 + (0 - 0)^2 + (0 - 0)^2 + (0 - 1)^2) \\
 &= 0.5.
 \end{aligned}$$

Such a loss is significant when the outcome is only 0 or 1. In this situation, the network must be trained to provide more accurate results. Calculus makes up these fundamental themes of machine training and learning.

4. Calculus and Machine Learning

In machine learning, the goal is to minimize the loss of accuracy of an artificial neural network. By re-examining the neural network, there are two inputs, each carrying a weight, going through a hidden layer with two neurons, and an output neuron from which the predicted gender value y_p is generated. The network is a chain of functions:

$$\begin{aligned}
 h_1 &= f_1(w_1x_1 + w_2x_2 + b_1), \\
 h_2 &= f_2(w_3x_1 + w_4x_2 + b_2),
 \end{aligned}$$

and

$$y_p = o_1 = f_3(w_5h_1 + w_6h_2 + b_3).$$

The predicted gender value y_p is a function of multiple variables: $w_1, w_2, w_3, w_4, w_5, w_6, b_1, b_2$ and b_3 . So is the loss function L ,

$$\begin{aligned}
 L &= MSE \\
 &= \frac{1}{n} \sum_{i=1}^n (y_t - y_p)^2 \\
 &= L(w_1, w_2, w_3, w_4, w_5, w_6, b_1, b_2, b_3).
 \end{aligned}$$

The loss function is influenced by weights and biases. One can find the minimum loss by choosing weights and biases wisely. From calculus, the optimized weights and biases can be found with the gradient descent method. To further simplify the discussion, assume that the dataset has only one individual, Carol. Then, the loss function is simplified to

$$L = MSE = \frac{1}{1} \sum_{i=1}^1 (y_t - y_p)^2 = (1 - y_p)^2.$$

The rate of change of the loss function with respect to w_1 is the partial derivative $\frac{\partial L}{\partial w_1}$. By the chain rule, this can be simplified into,

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_p} \cdot \frac{\partial y_p}{\partial w_1}.$$

From the simplified loss function, the result is,

$$\frac{\partial L}{\partial y_p} = \frac{\partial(1-y_p)^2}{\partial y_p} = -2(1-y_p).$$

Meanwhile from the function set of the network, the partial derivatives can be found as,

$$\begin{aligned} \frac{\partial y_p}{\partial w_1} &= \frac{\partial y_p}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1} \\ \frac{\partial y_p}{\partial h_1} &= w_5 f'(w_5 h_1 + w_6 h_2 + b_3), \end{aligned}$$

and

$$\frac{\partial h_1}{\partial w_1} = x_1 f'(w_1 x_1 + w_2 x_2 + b_1).$$

Keep in mind that f is the logistic function,

$$f(x) = \frac{1}{1+e^{-x}}.$$

Its derivative is from the chain rule again,

$$\begin{aligned} f'(x) &= -1(1+e^{-x})^{-2}(-e^{-x}) \\ &= \frac{e^{-x}}{(1+e^{-x})^2}. \end{aligned}$$

To summarize, the final equation is,

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_p} \cdot \frac{\partial y_p}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1}.$$

This process of calculating partial derivatives by working backward is known as **backpropagation**, or simply **backprop**. Backprop is all about calculus!

Finally, the network can be trained to learn from the dataset with only one individual, Carol. To get started, all weights are simply initialized as 1, $w_1 = w_2 = w_3 = w_4 = w_5 = w_6 = 1$, and biases, $b_1 = 2$, $b_2 = 1$ and $b_3 = 0$. After one round of **feedforward**, the consequential numbers are,

$$\begin{aligned} h_1 &= f(w_1 x_1 + w_2 x_2 + b_1) \\ &= f(-2 + (-1) + 2) \\ &= 0.2689, \\ h_2 &= f(w_3 x_1 + w_4 x_2 + b_2) \end{aligned}$$

$$= f(-2 + (-1) + 1) \\ = 0.1192,$$

and

$$y_p = o_1 = f(w_5 h_1 + w_6 h_2 + b_3) \\ = f(0.2689 + 0.1192 + 0) \\ = 0.5668.$$

The network output $y_p = 0.5668$, does not favor either 0 for male or 1 for female. To train the network, first round of **backprop** starts with the partial derivatives:

$$\frac{\partial L}{\partial y_p} = -2(1 - y_p) \\ = -2(1 - 0.5568) \\ = -0.8864,$$

$$\frac{\partial y_p}{\partial h_1} = w_5 f'(w_5 h_1 + w_6 h_2 + b_3) \\ = 1 \cdot f'(0.2689 + 0.1172 + 0) \\ = f'(0.3861) \\ = 0.2409,$$

$$\frac{\partial y_{h_1}}{\partial w_1} = x_1 f'(w_1 x_1 + w_2 x_2 + b_1) \\ = -2f'(-2 + (-1) + 2) \\ = -2f'(-1) \\ = -0.3932,$$

and

$$\frac{\partial L}{\partial w_1} = \frac{\partial L}{\partial y_p} \cdot \frac{\partial y_p}{\partial h_1} \cdot \frac{\partial h_1}{\partial w_1} \\ = (-0.8864)(0.2409)(-0.3932) \\ = 0.0837.$$

Because $\frac{\partial L}{\partial w_1} > 0$, the loss function L increases as w_1 increase. To reduce the loss, w_1 must be subsequently reduced. The gradient descent method enables the neural network to learn the optimal value of w_1 ,

$$w_1^{(1)} = w_1^{(0)} - \eta \frac{\partial L}{\partial w_1}.$$

In the update equation above, η is a positive constant, known as relaxation factor in math, or learning rate in AI. Given a large dataset, an artificial neural network can set its own learning rate that controls the pace of machine learning. Let $w_1^{(0)}$ denote the original value of w_1 , and $w_1^{(1)}$ to denote the updated value of w_1 . It's important to note that w_1 may increase

or decrease in either direction depending on the sign of $\frac{\partial L}{\partial w_1}$. If $\frac{\partial L}{\partial w_1}$ is positive, w_1 decreases, which makes the loss L decrease. If $\frac{\partial L}{\partial w_1}$ is negative, w_1 increases, which makes the loss L decrease again. The same process can be applied iteratively for every weight and bias on one sample and for every sample in the dataset. Ultimately, the neural network improves steadily as the loss decreases.

5. AI and Active Learning

Machine learning is an iterative process optimized with mathematical tools. In turn, AI-driven tools can provide an active learning environment in ways that other tools could not. AI tools offer high quality services continuously and consistently (Gardner, 2021). Their skills have been proven to facilitate learning and improve upon already advanced methods of learning. Within the classroom and from personal experience, students have successfully used AI as an effective study tool to boost their academic performance, increase comprehension of content and gain confidence in using technology to solve complex problems.

While mathematics is not often considered an exciting subject for many students, the rapidly growing use of AI within classrooms connects students with real world technology and simultaneously increasing their participation in classroom via hands-on learning. For instance, after learning derivatives and their applications in AI, students used their skills to identify the various elements of the mathematical tools for natural language processing. To form a sentence, AI selects the optimal word each round by calculating the minimum of the loss function, which is obtained by setting derivatives equal to zero. From derivatives to sentence generating, students demonstrated a stronger motivation to learn calculus as they realized its power in AI.

AI can be used to solve challenging problems. With help of AI, students built a model to predict the timeline to reduce pollution from a local lake. They were able to identify the various elements of the model, determine the values of specific components, and connect the model to a first order linear differential equation. Additionally, they were able to interpret and draw conclusions from graphs and numerical values. Moreover, students were able to summarize and justify analyses of the mathematical model for the lake pollution problem. And ultimately express those solutions by using an appropriate combination of words, symbols,

tables and graphs. AI certainly keeps students more engaged in learning complex subjects, such as differential equations.

For both classes involved, calculus and differential equation classes, with the use of AI, students demonstrated higher levels of motivation and better academic performance and engagement, compared to what was reported during previous classes.

AI can generate personalized learning experiences to meet the individual demands of students. They can produce multiple explanations for math concepts and formulas to students with different backgrounds (Shemshack et al., 2020). Meanwhile, AI tools present challenges to both educators and students. Depending on data collected and algorithm used, AI may provide inaccurate, or even false answers (Khosravi et al., 2022). Educators need to be more knowledgeable so they can detect anomalies in AI. While AI excels in solving computational problems, educators need to emphasize more on problem solving skills, (The National Research Council, 2013). As technology advances, it's time for educators to reimagine teaching and assessment. The use of AI within classrooms not only exposes students to the world of technology but also builds upon their current education in mathematics.

At the time this paper was prepared, two AI scientists were awarded the Nobel Prize in October 2024 (The Nobel Prize Press Release October 2024). Geoffrey Hinton, known as the godfather of AI, won in physics for inventing a method that can autonomously find properties in data. Demis Hassbis, cofounder of Google DeepMind, won in chemistry for his work in developing an AI model for predicting proteins' complex structure. The continuous success of AI will inspire a growing interest in mathematics for more and more students.

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