Assessing the Effectiveness of GenAI Tutoring for Tertiary Academic Probation Students: A Repeated Measures Study Using ChatGPT

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Abstract. Generative artificial intelligence (GenAI) has precipitately emerged as a transformative tool in higher education, particularly in student learning. This study investigates the efficiency of ChatGPT as a GenAI-assisted tutoring tool for academically at-risk students enrolled in IDS-097 Academic Accountability, a 1-credit intervention course designed to support students on academic probation. Using a quantitative repeated measures design, 50 students completed two equivalent exams: Exam #1 (without GenAI support) and Exam #2 (after utilizing ChatGPT as a studying and tutor aid). A paired-sample t-test revealed a statistically significant improvement in student performance ($t(49) = -8.21$, $p < 0.001$), with mean scores increasing from Exam #1: 72.1% (C) to Exam #2: 85.4% (B+) and demonstrating a large effect size (Cohen's $d = 1.13$). A Pearson correlation analysis ($r = 0.74$, $p < 0.001$) and pre- and post-surveys analyzed through Cronbach's Alpha ($\alpha = 0.93$) suggest a positive relationship between ChatGPT usage and learning gains. Findings align with the Technology Acceptance Model and Cognitive Load Theory, inferring that GenAI-assisted tutoring supports knowledge acquisition. Future research should investigate long-term memory retention for students, faculty-led GenAI support initiatives, and GenAI-incorporated tertiary studies utilizing broader student types for increased generalization.

Keywords: Generative Artificial Intelligence · ChatGPT · Tutoring · Studying

1 The Problem Addressed, State of the Art in AIED and its Relevance to Education

1.1 The Problem Addressed as Unstructured GenAI Utilization

As the Director of Academic Success at Cornerstone University, a private Christian liberal arts institution located in Grand Rapids, Michigan serving undergraduate and graduate students in traditional, adult, and online learning, the unstructured use of generative artificial intelligence (GenAI) by students in their academic coursework is increasingly becoming normalized. This occurrence is currently being assessed via two major initiatives. The first initiative is creating short-term guidance for both faculty and students. The Director of Academic Success has created the institution-wide policy "Generative

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AI and Academics", which provides directives on how GenAI can be used in coursework, assessments, and academic integrity compliance [1]. This policy is included in all syllabi at the institution and within the university's academic catalog. The second initiative is leveraging institutional leadership expertise and emerging GenAI technologies to design and implement structured GenAI usage procedures and integrated Gen-AI learning frameworks for higher education institutions.

1.2 State of the Art Regarding GenAI and AIED

The rapid proliferation of free, publicly accessible GenAI platforms such as the Chat Generative Pre-Trained Transformer (ChatGPT) has catalyzed a significant shift in the field of Artificial Intelligence in Education (AIED). While foundational advancements in large language models, natural language processing, and intelligent tutoring systems predate this technological surge, recent GenAI popularity and accessibility has amplified interest in their educational applications. Researchers Gligorea and Cioca claim that the intersection of GenAI and learning technologies enable higher education to balance innovation with institutional integrity, particularly through adaptive content generation and student engagement features [2]. Yan et al., in a controlled experimental study revealed that GenAI agents augmented with scaffolding mechanisms significantly improved students' comprehension of ophthalmic learning outcomes, highlighting the potential for GenAI within complex educational learning environments [3]. Despite this momentum, substantial pedagogical and ethical concerns persist. Al-Mamary et al. identified that while GenAI adoption is increasing among faculty and students, the absence of institutional clarity on academic integrity and coursework authorship has produced inconsistent usage policies and perceptions [4]. Zhang et al. provide a scoping review that outlines the evolving impact of GenAI on educational assessments, stressing the tension between automation and pedagogical authenticity [5]. These concerns are further researched in McDonald et al.'s analysis of institutional policy documents across U.S. universities, where the authors found that while many institutions acknowledge GenAI's instructional capabilities, few have developed actionable, detailed guidelines to support equitable and ethical adoption for students and faculty [6].

1.3 GenAI Impact on Higher Education Curricula and Learning

The popularity of GenAI and its availability to matriculated students has caused disruptions for both academic administrators and course instructors. When faculty design a course, it includes learning outcomes students should fully understand and grasp at the conclusion of the course. When students use GenAI to generate entire essays or answer prompts without engaging with course content, it bypasses the intended cognitive effort required by the assignment. For instance, instead of analyzing a case study to develop critical thinking skills, students could copy a ChatGPT-generated response to said case study, resulting in superficial understanding and reduced learning engagement, which may undermine intended learning outcomes in courses where original student synthesis and critical analysis are primary learning objectives.

2 Theoretical Framework and Research Design Approach

2.1 Theoretical Framework for GenAI Curricula Support

This study utilized an integrated theoretical framework combining four established models to evaluate the academic impact of GenAI support for students on academic probation. Each model contributes a complementary lens: Bloom's Revised Taxonomy (BRT) provides a cognitive scaffolding to categorize and interpret the complexity of student responses in distinguishing between lower-order (e.g., recall) and higher-order (e.g., synthesis, evaluation) learning [7]. While not originally designed for GenAI, BRT serves as a heuristic framework to analyze student outputs across varying cognitive levels. Vygotsky's Zone of Proximal Development (ZPD) is adopted conceptually to frame the notion of "instructional scaffolding"—a role now mirrored in GenAI-assisted learning where GenAI provides dynamic prompts that adapt to students' inputs [8]. It is acknowledged that ZPD predates GenAI and does not natively support machine-mediated instruction, yet its foundational emphasis on learner support within an optimal developmental zone remains relevant. To assess the adoption and engagement with GenAI software, the Technology Acceptance Model (TAM) is employed to evaluate two key constructs: perceived usefulness and ease of use. These variables help explain students' willingness to incorporate GenAI into their study practices and the extent to which it influences their academic motivation [9]. Finally, Cognitive Load Theory (CLT) supports an analysis of how GenAI may or may not minimize extraneous cognitive load, which refers to unnecessary mental effort often caused by unclear instructional delivery or cognitively inefficient learning materials, while enhancing germane load, which supports schema construction and intentional learning [10].

2.2 Methodology: Repeated Measures Design and Exam Structure

This study employed a repeated measures design involving 50 students on academic probation enrolled in a required academic accountability course. All 50 students completed both assessments: Exam 1 without any GenAI support and Exam 2, one-week later, after structured tutoring engagement with ChatGPT as a study aid. The exams covered identical neuroscience content related to learning mechanisms such as neuron structure, synaptic transmission, neuroplasticity, and the role of the hippocampus in memory, but used different question formats to minimize memorization effects. Specifically, Exam 1 employed multiple-choice questions (MCQs) for foundational recall and short-answer questions (SAQs) for applied reasoning; in Exam 2, the formats were reversed (SAQs for recall, MCQs for application), ensuring equivalent cognitive demands while preventing direct repetition. This "MCQ-SAQ flip" stratagem was implemented to reduce test familiarity bias and emphasize conceptual understanding [11]. Additionally, all students were given a PDF study guide with specific instructions on prompt engineered questions [12] to ask ChatGPT to aid in studying exam content (Figs. 1 and 2).

2.3 Additional Research Study Factors and Future Considerations

Implementing GenAI within a higher education context requires more than access to software interfaces; it requires structured leadership, thoughtful pedagogy, and what scholars

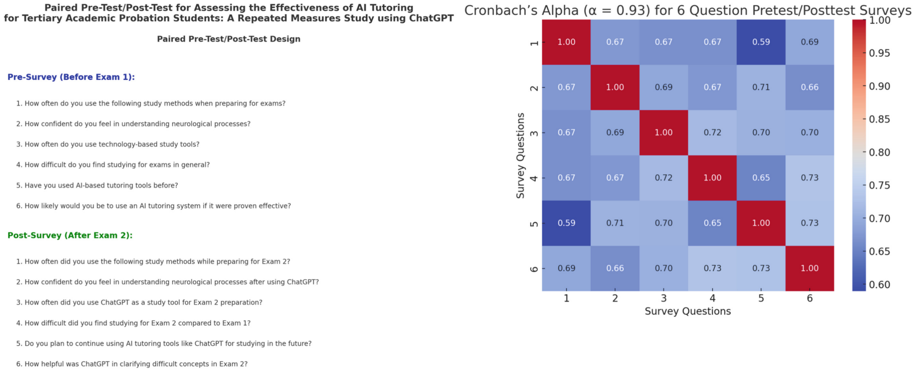

Fig. 1. A display of the paired pre- and post-survey questions used to assess changes in study behaviors, academic confidence, and perceptions of GenAI. Inter-item correlations shown in the heatmap indicate strong internal consistency, with a Cronbach's Alpha of α = 0.93, validating the reliability of the instrument in evaluating the effects of ChatGPT tutoring.

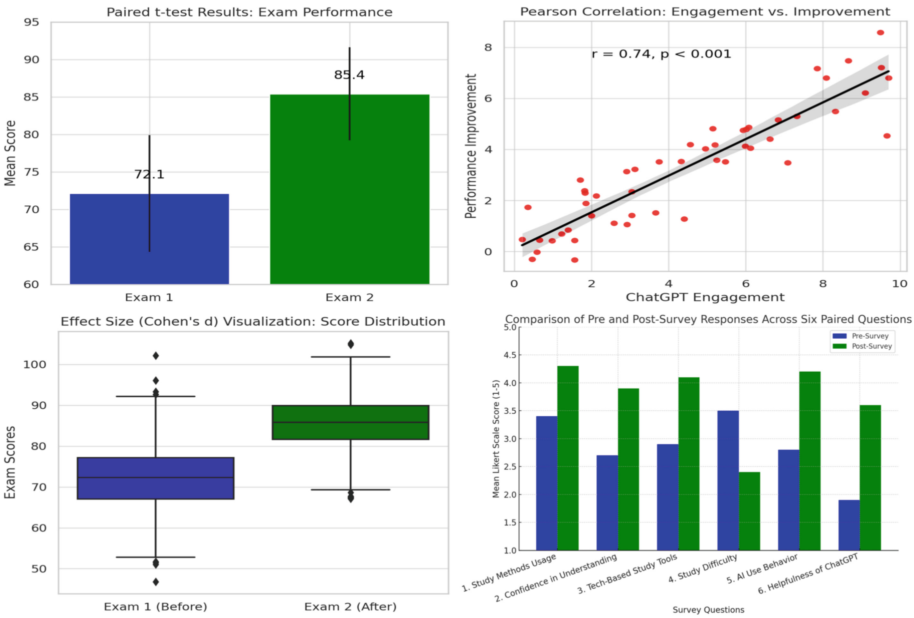

Fig. 2. Exam average scores improved from 72.1 (C) to 85.4 (B+): (t(49) = –8.21, p < 0.001), with a strong correlation between ChatGPT usage and performance gains (r = 0.74, p < 0.001). A large effect size (Cohen's d = 1.13) and Likert-scale paired pre- and post-survey results verified post-intervention gains in study behavior, confidence, and GenAI expediency.

increasingly refer to as AI literacy—a working understanding of how AI systems function, their ethical constraints, and their responsible application in academic settings. In this study, the Director of Academic Success, serving also as the instructor for IDS-097

Academic Accountability, facilitated the intervention by designing a five-page neuroscience study guide aligned with course content and demonstrating how to integrate it into ChatGPT. Students were shown prompt engineering techniques [12] to generate custom practice questions and were instructed to verify GenAI outputs against course textbooks and materials to reinforce content accuracy. Further dissertation research must expand on this study by including a randomized control trial structure, longitudinal retention tracking, validated instruments for cognitive and behavioral measures, and broader student sampling across disciplines and academic standings.

3 Contributions and Impact of Research to AIED

3.1 Learning Sciences and Future AIED Research Direction for GenAI

The learning science domain encompasses studies on how individuals learn and how instructional methods, technologies, and environments can be designed to enhance learning outcomes by integrating research from cognitive science, educational psychology, artificial intelligence technology, and social learning theories [13]. Learning sciences also examines theories of learning such as constructivism, TAM, and CLT—the latter two cited in this piloted research study. Many empirical research studies on GenAI's intersection within education neither focus on integrative incorporations nor are there a substantial amount of longitudinal research studies available. Throughout the Ed.D. program, the Director of Academic Success is committed to assisting fill this identified research gap by designing intentional research studies and collaborating with researchers, educators, instructional designers, data scientists, and key GenAI stakeholders throughout his dissertation process. GenAI and computer science are interconnected entities, from machine learning and deep learning using neural network architectures such as transformers, generative adversarial networks, and diffusion models [14], to more technical specs such as software engineering and programming to automate code generation, refactoring, and debugging [15]. A contribution to the computer science domain would be focused research on the human-centric nature of GenAI as a supplementary tool, not a primary replacement for human-driven work [16]. Additionally, checks and balances must be imposed within GenAI frameworks to ensure that machine learning databases are filled with equitable data that is culturally sensitive to diverse users, is fully accessible to persons with disabilities, expand language options to increase the populations of users and researchers, ethically and securely stores data in cloud and physical servers that are protected from data breaches, and prioritize GenAI-related support to at-risk populations [17] such as intentional GenAI support instruments for students facing adverse academic difficulties.

References

1. Cornerstone University: "Generative AI." Academic Policies & Procedures. https://catalog.cornerstone.edu/academics/policies-procedures/generative-ai/. Accessed 11 May 2025
2. Gligorea, L., Cioca, L.: Generative AI in higher education: Balancing innovation and integrity. Br. J. Biomed. Sci. (2024). https://www.frontierspartnerships.org/journals/british-journal-of-biomedical-science/articles/10.3389/bjbs.2024.14048/full

3. Yan, L., et al.: The effects of generative AI agents and scaffolding on enhancing students' comprehension of visual learning analytics. arXiv preprint arXiv:2409.11645 (2024). https://arxiv.org/abs/2409.11645
4. Al-Mamary, Y.H., Alfalah, A.A., Shamsuddin, A., Abubakar, A.A.: Generative AI and the future of higher education: a threat to academic integrity? Int. J. Educ. Technol. High. Educ. **21**, 1–15 (2024). https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-024-00453-6
5. Zhang, Y., Li, X., Wang, H.: A scoping review on how generative artificial intelligence transforms assessment in higher education. Int. J. Educ. Technol. High. Educ. **21**, 1–20 (2024). https://educationaltechnologyjournal.springeropen.com/articles/10.1186/s41239-024-00468-z
6. McDonald, N., Johri, A., Ali, A., Hingle, A.: Generative artificial intelligence in higher education: evidence from an analysis of institutional policies and guidelines. arXiv preprint arXiv:2402.01659 (2024). https://arxiv.org/abs/2402.01659
7. Anderson, L.W., Krathwohl, D.R.: A taxonomy for learning, teaching, and assessing: a revision of Bloom's taxonomy of educational objectives. Longman (2001)
8. Vygotsky, L.S.: Mind in Society: The Development of Higher Psychological Processes. Harvard University Press (1978)
9. Davis, F.D.: Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. **13**(3), 319–340 (1989)
10. Sweller, J., Ayres, P., Kalyuga, S.: Cognitive load theory. Springer (2011). https://doi.org/10.1007/978-1-4419-8126-4
11. Roediger, H.L., Karpicke, J.D.: Test-enhanced learning: taking memory tests improves long-term retention. Psychol. Sci. **17**, 249–255 (2006)
12. Korzyński, P., Mazurek, G., Krzypkowska, P., Kurasiński, A.: Artificial intelligence prompt engineering as a new digital competence: analysis of generative AI technologies such as ChatGPT. Entrep. Bus. Econ. Rev. **11**(3), 25–38 (2023)
13. Bates, A.W.: Managing Technological Change: Strategies for College and University Leaders. Jossey-Bass (1999)
14. Greeno, J.G., Engeström, Y.: Learning in activity. In: Sawyer, R.K. (ed.) The Cambridge Handbook of the Learning Sciences, pp. 128–147. Cambridge University Press (2014)
15. Vaswani, A., Shazeer, N., Parmar, N., et al.: Attention is all you need. In: Advances Neural Information Processing System, vol. 30 (2017)
16. Riedl, M.: Human-centered artificial intelligence and the future of generative AI. AI Soc. **37**, 435–449 (2023)
17. Zawacki-Richter, O., Jung, I., Bond, M., et al.: Practical and ethical challenges of large language models in education: a review of ChatGPT in teaching and learning. Br. J. Educ. Technol. **54**(6), 1245–1264 (2023). https://doi.org/10.1111/bjet.13370