Educational Technology Quarterly, Vol. **2025**, Iss. 1, pp. 1–15 https://doi.org/10.55056/etq.788

A proposed framework for achieving higher levels of outcome-based learning using generative AI in education

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Abstract. Generative artificial intelligence (GAI) systems like ChatGPT have gained popularity due to their ability to generate human-like text. Educators are exploring how to leverage these systems to facilitate and promote learning and develop skills and abilities. This study proposes a conceptual framework aimed at facilitating outcome-based learning through the utilization of GAI tools. The overall aim of this study is to provide a way for integrating GAI to support outcome-based education paradigms focused on learning objectives by aiding cognitive ability development according to Bloom's taxonomy. This paper introduces a framework called the ACE Framework (AI-Enhanced Cognition for Outcome-Based Learning), which organizes the integration of emerging large language models to facilitate advanced analysis, synthesis, and evaluation, as defined by Bloom's taxonomy, from basic knowledge recall to complex conceptualization. To empirically assess the effectiveness of unaided and GAI-assisted approaches, an analysis of real-world scenarios was conducted, where 20 college students created open-ended written solutions. For every response set, human raters classified shown cognitive abilities into Bloom's levels. In structured GAI integration exercises, participants learnt about problems using models such as GPT-4 and framed analytical answers. Comparative benchmarking reveals significant enhancements in average ratings from predominant comprehension (3.35) to top-tier synthesis (4.85) after AI scaffolding based on the methodology. With six students reaching the highest evaluation tier, guided AI interactions showcase excellent ability to promote outcome-based learning. Despite limitations in sample size and assessment techniques requiring further investigation, results align with priorities of outcome-driven education models prioritizing higher-order cognition – substantiating structured AI incorporation potential.

Keywords: generative AI, Bloom's taxonomy, outcome-based learning, higher-order thinking, higher education

1. Introduction

The advent of large language models and generative AI (GAI) represents a pivotal moment for integrating emerging technologies into education to enrich learning [17]. As these systems improve in contextual reasoning and language sophistication, they must be aligned with key educational goals, such as boosting critical thinking and skill-based learning among students [7]. This study investigates a framework infused with GAI to promote complex learning. It concludes that, as language generation platforms advance, careful assessment is needed to leverage best practices in educational frameworks fully.

Bloom's taxonomy, published for the first time in 1956 [10], remains a prevalent framework within education, organizing learning outcomes or objectives from lower to

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higher cognitive skills, ranging from basic factual recall to advanced evaluation abilities [22]. This taxonomy has structured years of pedagogical and assessment design aimed at promoting cognitive abilities beyond simple fact memorization. Similarly, outcome-based education models focus on demonstrating tangible improvements in students' critical thinking and creative problem-solving competencies rather than relying on input-focused approaches. Outcome models also highlight the importance of clear metrics and rubrics to measure success, as seen through learning taxonomies [6]. Thus, intensifying dynamic teaching activities to support sequential skill development is appropriate within outcome-based education settings. Generative AI shows promise in areas such as summarization and content knowledge, but its potential for enabling near-human-like higher-order skills, as outlined by Bloom's taxonomy, needs to be quantified [20]. Given the lack of formal methods to leverage GAI for achieving complex, high-level learning outcomes needed in outcome-based education, this research becomes crucial. Strategic mapping of GAI's evolving capabilities can provide insights to enhance students' cognition through intentional technology integration as the learning experience undergoes a paradigm shift.

This study puts forth and tests an innovative generative AI-enabled learning framework to incorporate GAI tools into education, with the goal of supporting students in progressively attaining sophisticated learning outcomes aligned to the highest levels of thinking skills conceptualized in Bloom's taxonomy of knowledge, comprehension, application, analysis, synthesis, and evaluation. The overarching research question guiding this investigation is: *How can GAI be effectively integrated based on a structured methodology to promote outcome-based learning?*

The knowledge gap in this area reaffirms the need for a comprehensive, systematic approach that not only embeds GAI into education but also enhances students' skills, particularly in Bloom's higher-order cognitive categories. This study aims to bridge this gap by introducing and testing the ACE Framework (AI-Enhanced Cognition for Outcome-Based Learning), which specifically integrates generative AI into educational activities to promote critical analysis, synthesis, and evaluation skills among students. This research will contribute to the AI education literature and provide educators with a structured method for purposefully incorporating these tools to achieve outcome-based learning objectives.

The study's central contribution is a six-stage generative AI-enabled Learning Framework. In an empirical assessment involving twenty students, this approach demonstrated measurable improvements in Bloom's taxonomy dimensions, serving as the target benchmark. These findings address an important research gap in optimizing responsible and ethical AI integration for enhancing outcome-driven education focused on human-like cognition. The framework offers a transferable structure for applying GAI advances to support learning outcomes.

2. Literature review

The integration of emerging technologies like generative AI into education to enrich learning outcomes is an active area of research [4, 14]. Recent studies have begun exploring applications of large language models such as GPT-4 for writing support and feedback [15]. Recent systematic reviews, such as [5], have extensively analyzed the use of AI in primary education. This study highlights various pedagogical approaches and categorizes them into constructive learning experiences, including project-based learning and interactive engagement. Another systematic review [3] explored the opportunities, challenges and student perception of integrating GAI tools in education settings. However, there has been limited investigation into whether these advanced natural language systems can help students achieve higher-order thinking skills aligned with learning objectives. Some studies have analyzed ChatGPT's capabilities for academic writing tasks compared to human performance. Studies have tested its skills in summarizing, assessing essay quality, and formulating research questions, finding strengths in summarization but gaps in higher-level analysis [9]. Another study Lavidas et al. [16] provides a detailed exploration of the factors influencing humanities and social sciences students' intentions to use AI applications in academic settings. Utilizing the UTAUT2 model, their findings emphasize the role of performance expectancy, habit, and enjoyment, shedding light on the psychological and behavioural aspects of AI adoption among students. This study enriches our understanding of how different academic disciplines may perceive and integrate AI tools, which is crucial for developing tailored educational technologies. In their study, the authors put forth and tested a 6-stage framework called "AI-CRITIQUE" designed to integrate AI tools like ChatGPT into higher education in a way that enhances critical thinking abilities [25]. An empirical study was conducted with 20 students who answered an opinion-based question with and without ChatGPT following the proposed framework. Using Lee's thinking level model, the analysis showed that students' average thinking level improved from basic recall (1.35) to more rationalization (2.4) when utilizing ChatGPT and the framework. Additional survey data revealed that students felt ChatGPT helped boost their ideation, creativity, and critical analysis compared to working solo.

Bloom's taxonomy provides a hierarchical model for classifying learning objectives and outcomes according to cognitive skill complexity needed for students to demonstrate their capability (table 1). Taxonomy categorizes thinking abilities on a spectrum spanning lower-order cognition, like basic fact and information recall, to high-order skills that include critical analysis, a novel application, and evaluative judgments. The six classifications, beginning from the lowest, are – Knowledge, Comprehension, Application, Analysis, Synthesis, and Evaluation. Knowledge relates to memorization and rote learning, while Comprehension refers to demonstrating understanding through activities like explaining, comparing, and interpreting given material. The Application utilizes information to solve real-world problems in new scenarios, while the Analysis breaks down content to make inferences and identify evidence to derive conclusions. Synthesis involves building connected and coherent ideas from disparate

Table 1
Bloom's taxonomy.

Levels of thinking	Degree of levels	Category	Description
Level 1	Lowest	Knowledge	Basic recall, recognition, and memorization of facts, information, and concepts
Level 2	Intermediate	Comprehension	Demonstrating a basic understanding of facts and ideas by being able to summarize, interpret, compare, and contrast.
Level 3		Application	Using information and conceptual knowledge in real-world situations and novel contexts.
Level 4		Analysis	Breaking down information into component parts, making inferences, and finding evidence and relationships to support generalizations.
Level 5		Synthesis	Building a connected whole from diverse elements and parts. This includes activities such as producing plans and proposals or designing creative outputs.
Level 6	Highest	Evaluation	Making evidence-based judgments on concepts against defined criteria and rationale.

elements and sources. Finally, Evaluation represents demonstrating capacity for judgments based on in-depth, evidence-based reasoning aligned to criteria. Blooms thus create a definitive scaffold for delineating and designing learning objectives as well as assessments with increasing complexity and sophistication of critical thinking abilities. Educators often use Bloom's to foster higher-order cognition among learners.

Bloom's taxonomy has been used extensively for developing and classifying learning outcomes in education contexts [18]. However, no research has been conducted to measure the development of the cognitive ability level of students using GAI tools as assistance. Moreover, it is necessary to evaluate the effect of GAI in the context of the outcome-based learning environment. The growing focus on outcome-based learning and education emphasizes the need for concrete student competencies, skills, and abilities as measures for academic success [12]. As opposed to inputs-based approaches that focus on resources, outcome models start with clearly defined learning objectives, goals, and outcomes as guiding metrics. The desired outcomes across knowledge, attitudes, and higher-order thinking then shape teaching and assessment strategies. Since generative AI systems already show promise in some competencies like summarization and content knowledge, there is impetus to explore their potential in supporting the attainment of complex, human-like skills as defined by frameworks like Bloom's taxonomy. The ability to exhibit and facilitate higher cognitive abilities could make these AI tools more compatible with outcome-based education paradigms. Mapping generative AI's capabilities to learning taxonomies can uncover strengths, gaps, and opportunities to elevate students' learning outcomes amidst the responsible integration of emerging technologies. Though there have been studies to build frameworks like "AI-CRITIQUE" [25], "PAIGE" [24], and "IDEEE" [26] to integrate GAI in education none of them focuses on outcome-based education.

So, in this study, we propose a framework to achieve outcome-based learning with the integration of GAI in education. By systematically evaluating student-generated text, this innovative application of generative AI could provide key insights into its possibilities for facilitating complex, outcome-based learning aligned to Bloom's. The findings stand to inform responsible design decisions for integrating AI into education.

3. Methodology

Figure 1 illustrates the overall methodological strategy of this study, which consists of a literature review, a survey, an evaluation of the proposed framework, and a result analysis.

The research procedure consisted of three phases: preparation, implementation, and evaluation. In the preparation phase, 20 undergraduate students from the same academic background were selected, provided with technical texts, and briefed on the tasks. Students participated in two sessions during the implementation phase: one in which they answered open-ended questions without the aid of AI and another in which AI supported their learning by employing the ACE framework to improve cognitive abilities like synthesis and analysis. During the AI-assisted session, generative AI technologies were used in an organized manner to produce insights and improve responses. Finally, in the evaluation phase, the students' responses were scored using Bloom's taxonomy rubrics, comparing cognitive performance in both sessions. Statistical analysis was conducted, and qualitative feedback was collected to assess the AI's effectiveness in promoting higher-order thinking.

3.1. ACE Framework: AI-Enhanced Cognition for Outcome-Based Learning

The proposed framework (ACE Framework: AI-Enhanced Cognition for Outcome-Based Learning) has six sequential stages. Figure 2 depicts the proposed framework.

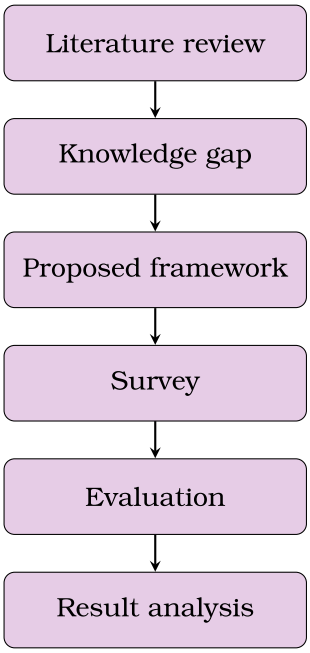


Figure 1: Methodological strategy.

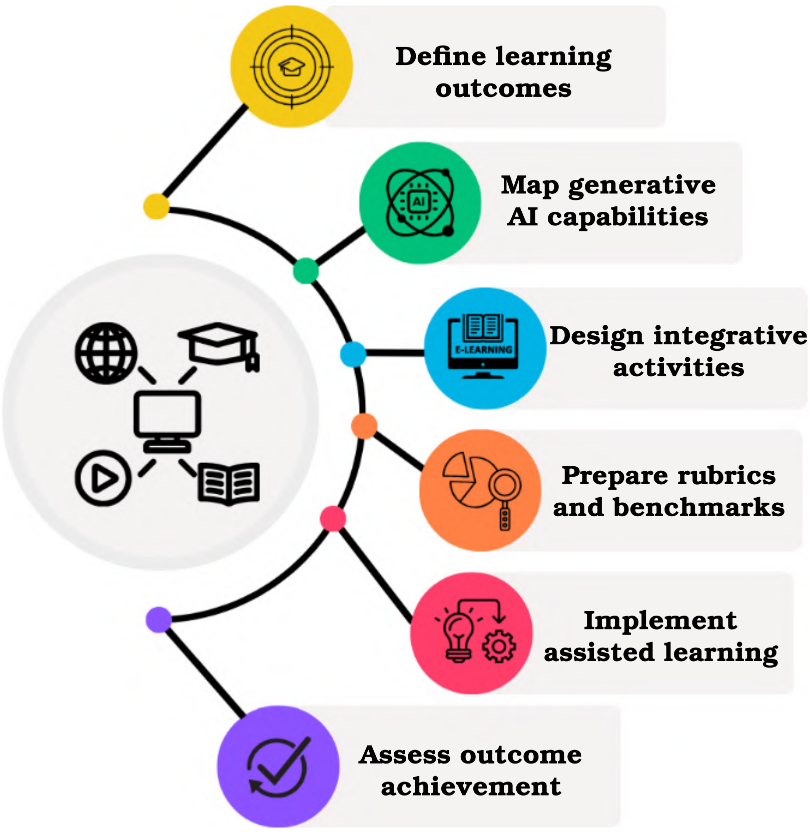


Figure 2: Proposed framework (ACE Framework).

1. *Define learning outcomes*

The first step is to clearly identify and define the learning outcomes that students should achieve from a course or curriculum based on Bloom's taxonomy or other relevant frameworks [1]. These should emphasize higher-order thinking skills such as analysis, evaluation, and creation rather than just knowledge recall. The outcomes serve as a guiding structure.

2. *Map generative AI capabilities*

Analyze the latest capabilities of leading generative AI systems such as GPT-4, PaLM, and Claude 3.5 across different tasks and competency areas. We selected GPT-4 due to its advanced linguistic processing capabilities, which are critical for educational applications aiming to improve cognitive skills. The tasks and prompts used during the AI-assisted learning phase are detailed here, showcasing examples that illustrate how these tools were integrated to foster higher-order thinking and learning. Identify strengths and limitations specifically in facilitating higher cognitive abilities as defined in Bloom's taxonomy. This gap analysis informs responsible integration. The study recognized the inherent limitations in existing public benchmarks and the challenges of evaluating AI models for educational purposes. Most available benchmarks, such as those used to evaluate language models, are designed for general-purpose tasks like text generation, summarization, and question answering, which do not always align with the specific cognitive skill development targeted by Bloom's taxonomy. To address this, the study implemented a gap analysis to identify where these benchmarks fell short, particularly in areas like critical thinking, synthesis, and evaluation. Additionally, the research team carefully selected AI models known for their contextual understanding, such as GPT-4, but emphasized that these models were used with caution due to their lack of transparency, especially concerning training data.

3. *Design integrative activities*

Design student activities and assignments that integrate generative AI tools in a targeted way to support achieving the defined learning outcomes [11]. Activities should be designed to capitalize on AI strengths while mitigating limitations [3, 8, 23] – for example, prompt formulation tasks to produce analytical responses rather than just text generation.

4. *Prepare rubrics and benchmarks*

Establish rubrics, success criteria, and benchmarks to assess student competency levels in outcome areas with and without AI assistance [13]. Rubrics help map progress on outcome-based learning metrics. Comparative benchmarking allows the evaluation of generative AI's efficacy.

5. *Implement assisted learning*

Implement the designed learning activities across student groups, providing access to selected generative AI tools [19, 21]. Build mechanisms to improve activity and prompt design based on rubric outcomes continually.

6. *Assess outcome achievement*

Systematically assess student work samples with and without AI assistance using the prepared rubrics. Compare ratings and benchmarks to evaluate generative AI's impact on achieving learning outcomes aligned to higher cognitive abilities in Bloom's taxonomy.

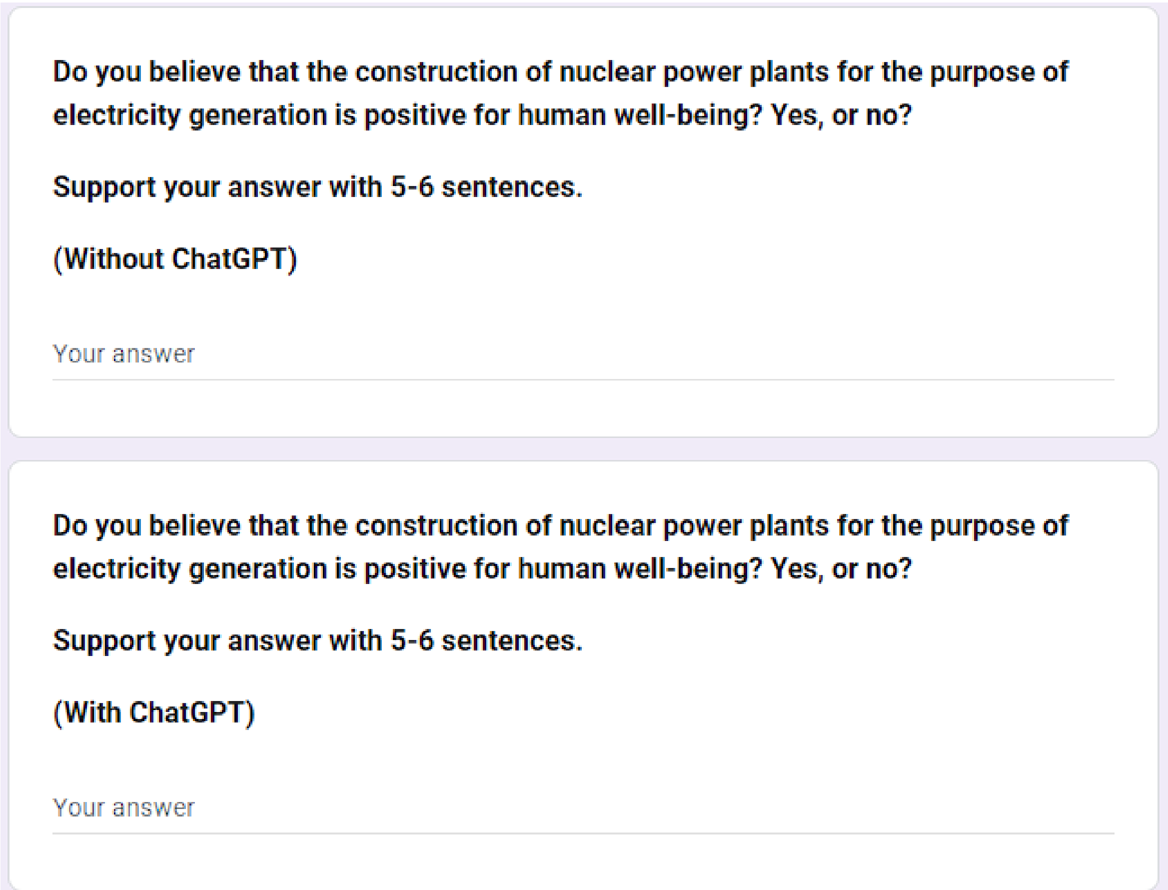
The outlined 6-stage framework for integrating generative AI tools in order to improve outcome-based learning provides multiple advantages. Firstly, by aligning activities and assessments to learning taxonomies like Bloom's, the approach promotes the development of higher-order cognition, including critical analysis, evaluation, and creative skills rather than just shallow information recall. Secondly, the entire process is anchored in predefined student learning outcomes, ensuring AI integration supports rigorous pedagogical goals rather than functioning as an add-on. This upholds educational integrity. In addition, the analysis of AI's evolving capabilities allows for precise and optimized targeting to balance strengths and limitations [27]. Accordingly, effectiveness may be assessed empirically by measuring the impact on outcomes using benchmarks. Moreover, the findings emphasize a principled approach to responsibly and ethically incorporating new technologies for learning, avoiding over-reliance on AI. Ongoing capability monitoring ensures that the framework stays agile and adaptable to cutting-edge advancements.

4. Survey

The sample size of 20 students was selected as part of an exploratory phase aimed at gathering initial insights into the efficacy of the ACE Framework in enhancing learning outcomes. The study, as a preliminary investigation, did not aim to generalize findings across a wide population but focused on (I) testing the framework's applicability and (II) identifying potential areas for improvement. It explored the relationship between AI generative capabilities and educational cognitive skills within a controlled cohort, specifically mapping AI abilities to Bloom's taxonomy. Additionally, the survey was crucial in assessing student performance with and without AI support, providing key data for future, larger-scale studies. The participants consisted of 12 males and 8 females, with almost all having academic backgrounds in computer science. This study is a preliminary exploration, not intended to generalize findings across populations but rather to test the framework and identify areas for improvement. With a well-defined cohort, the focus was on how this framework influenced cognitive skill development, particularly in applying generative AI at different levels of Bloom's taxonomy. The survey was a critical tool for measuring the framework's effect on student performance, comparing outcomes with and without AI assistance. This provided preliminary data for future larger-scale studies. The participants included 20 computer science students (12 males and 8 females), with a focus on analyzing responses to a real-world journal article through an open-ended opinion question, emphasizing reasoning over fact recall [2]. Students first independently formulated an answer without any AI tools, allowing internet access for supplementary information. This enabled establishing a baseline skill level. The same cohort then utilized GAI tools by following the framework to prompt the AI, learn more about the issue, ideate responses, and finally construct their answer, now integrating the generative capabilities. In this study, the decision to utilize a single journal article was made to focus the research scope and deepen the analysis within a controlled educational setting. The article was selected for its complexity and relevance to the course material, requiring students to engage in deep analysis and critical thinking. Concentrating on one article allowed us to meticulously analyze the students' ability to engage in deep analytical and critical thinking, essential skills in their field of study.

Students were specifically told to use numerous trustworthy sources to cross-verify the information produced by the generative AI tool during the evaluation and analysis step. To ensure accuracy and legitimacy, they were urged to evaluate AI-generated content rigorously by contrasting it with scholarly databases, peer-reviewed journal papers, and validated web sources. Students were urged to analyze the content by challenging the coherence and logic of AI responses, recognizing biases, and contrasting findings with the subject matter's larger context. This strategy sought to guarantee that students' final assessments were founded on verified data rather than just AI deductions and to lessen the possibility of AI hallucinations, which are frequent in big language models. They were also advised to use citation tools and reference management systems to document their sources, adding accountability and transparency to their analytical process.

Student responses were evaluated both times using defined rubrics grounded in Bloom's taxonomy to categorize thinking demonstrated into Knowledge, Comprehension, Application, Analysis, Synthesis, or Evaluation – comparative benchmarking quantified changes in measured cognition complexity with or without generative AI assistance. The empirical results stand to inform the framework's efficacy in elevating students along the learning taxonomy towards higher-order skills through guided and scaffolded AI incorporation activities framed around outcome achievement. This experimental research builds on established learning taxonomies and outcome-based education theory by embedding target outcomes, benchmarks, and consistent measurement mechanisms. The insights can uncover strengths and limitations to shape responsible integration models. A Google form was created and delivered to the participants so they could record their answers. Figure 3 depicts the survey form provided to the students to gather their answers.


Do you believe that the construction of nuclear power plants for the purpose of electricity generation is positive for human well-being? Yes, or no?

Support your answer with 5-6 sentences.

(Without ChatGPT)

Your answer

Do you believe that the construction of nuclear power plants for the purpose of electricity generation is positive for human well-being? Yes, or no?

Support your answer with 5-6 sentences.

(With ChatGPT)

Your answer

Figure 3: Survey form.

5. Result analysis

The study aimed to see if using AI tools can help improve students' critical thinking abilities. 20 undergraduate students first read an article and answered an open-ended question on their own without any AI help. Their answers were rated using Bloom's taxonomy scale to evaluate their learning outcome.

Next, the students used the GAI tool powered by a structured technique to learn more, generate ideas, and frame their answers to the same question. These AI-assisted responses were again scored by human experts on Bloom's scale. When both sets of scores were compared, it was found that with guided use of GAI as per the defined framework, students showed improvement in their average thinking levels. Unaided responses indicated basic understanding, while AI-supported answers demonstrated more logical reasoning and analysis. This suggests that if thoughtfully integrated following an appropriate scaffolding approach, generative AI tools can assist students in strengthening high-level thinking abilities linked to learning objectives. The before and after Bloom's ratings created an evidence-based benchmark to quantify the degree of improvement attributable to responsible AI augmentation. Figure 4 depicts a sample assessment result.

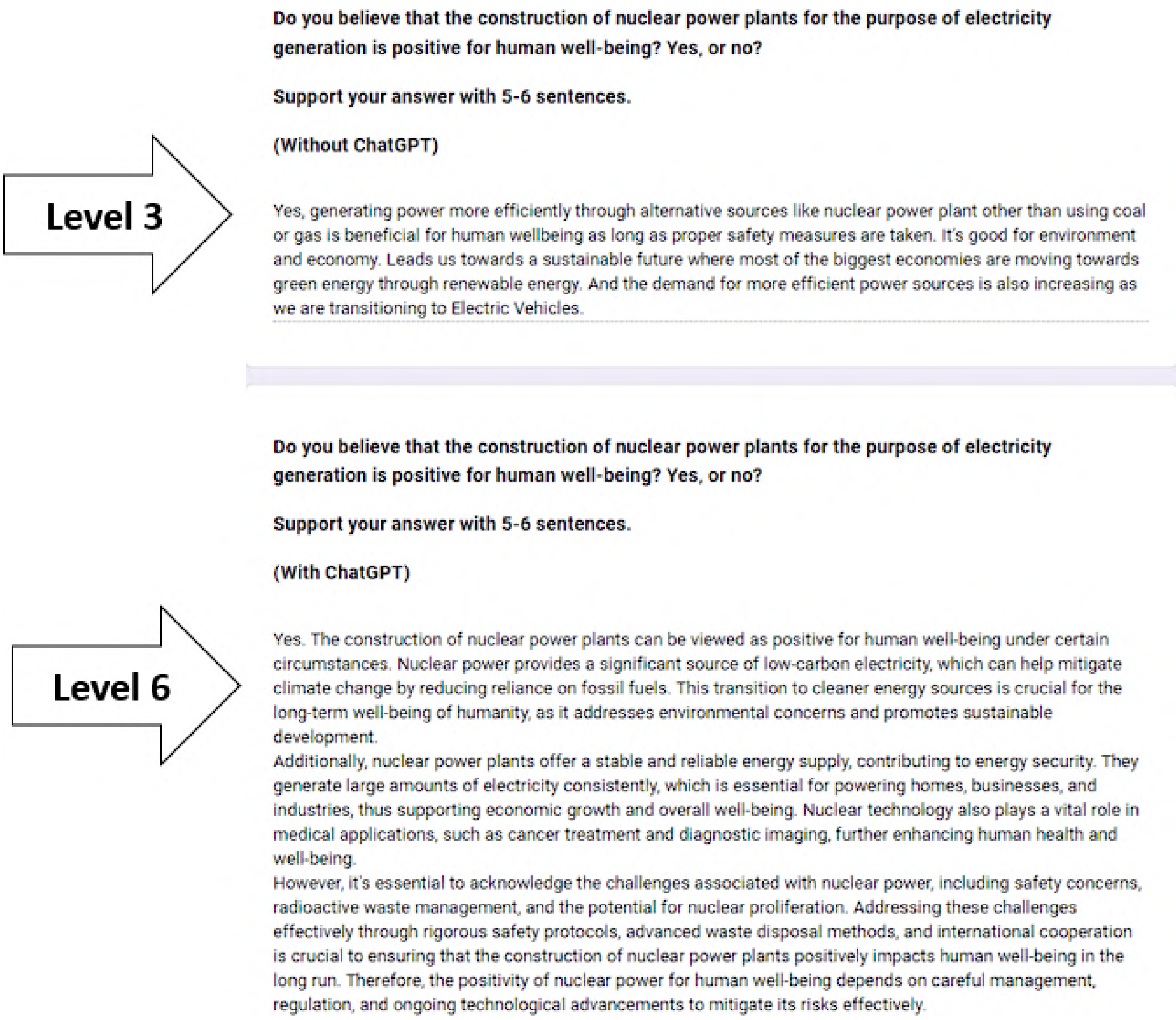


Figure 4: Sample evaluation result.

Figure 5 displays the assessment results of 20 students' answers without utilizing generative AI tools, evaluated per Bloom's taxonomy of educational objectives. The distribution indicates limited higher-order thinking – only one student reached the Synthesis level (level 5), and no students demonstrated Evaluation skills (level 6). Specifically, the majority of scores (11 instances) fell in the Comprehension range (level 3), followed by seven instances of Analysis skills (level 4).

In contrast, figure 6 illustrates remarkably improved assessment ratings after students interfaced with generative AI tools based on the proposed framework. The results

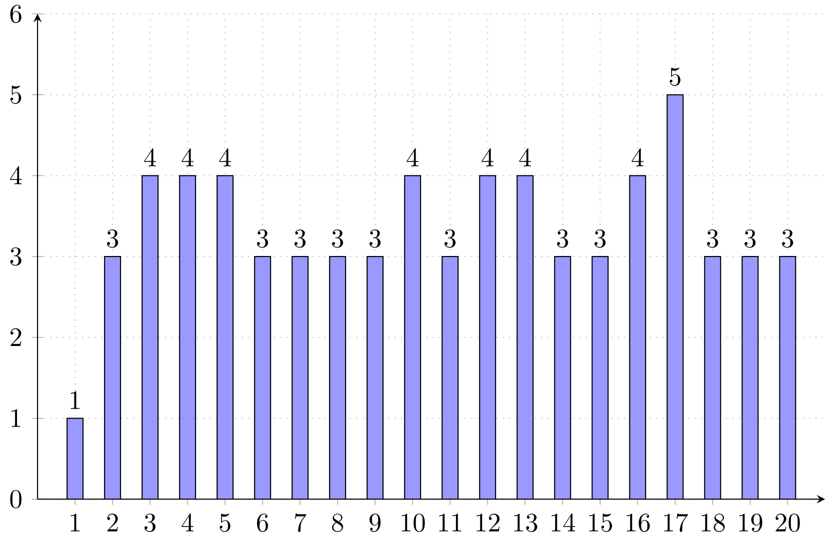


Figure 5: Evaluation result of 20 students (without AI assistance).

showcase successful scaffolding to higher levels of Bloom's taxonomy – 7 students produced work reflecting Synthesis skills (level 5), and 6 students demonstrated the highest order Evaluation abilities (level 6). With 6 students still in the Application and Analysis range (levels 3 and 4), there is an indication that generative writing aids may have differential impacts depending on the individual. Further research should investigate student factors that could moderate the relationship between generative scaffolds and response sophistication. Nonetheless, the sizeable elevation in top-tier thinking skill levels promotes the framework's generative writing supports as a promising avenue for achieving learning outcomes.

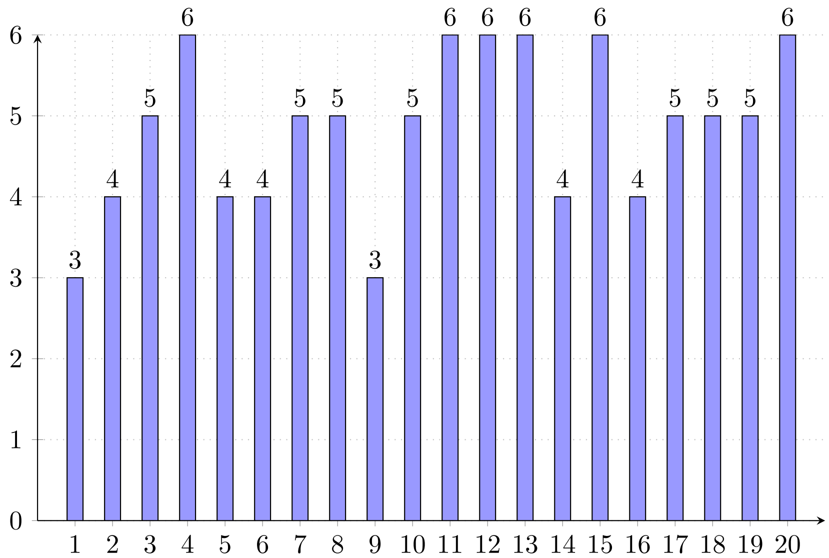


Figure 6: Evaluation result of 20 students (with AI assistance).

6. Discussion

Figure 7 illustrates the mean thinking skill level achieved by students on a set of open-ended responses, as evaluated through the lens of Bloom's taxonomy of educational objectives. Two conditions were compared: unaided responses constructed solely by students versus aided responses composed with the assistance of generative AI scaffolds. Responding without support tools, students demonstrated a mean score of 3.35, which aligns closest to the Application level of cognitive complexity. This signifies a capacity to adapt and employ knowledge to novel situations. In contrast, when interfacing with AI aids based on the proposed framework, the average score elevated significantly to 4.85. Such level maps are closest to the Synthesis skills of combining component ideas and information to build connected wholes. The sizeable increase from unaided responses to AI-assisted responses suggests that generative writing scaffolds may enable students to reach more advanced levels of conceptualization and thinking. Rather than simply applying isolated knowledge, the AI supports seemingly facilitated synthesizing connections across concepts the students possessed.

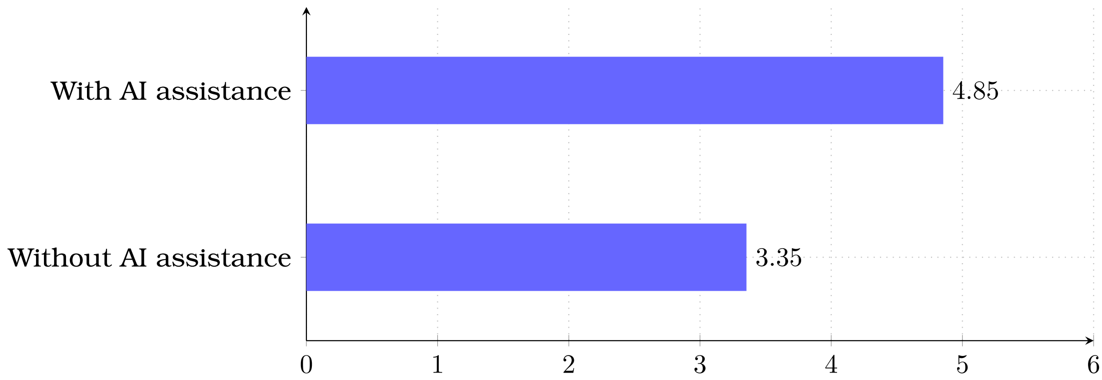


Figure 7: Average evaluation result (with and without AI assistance).

In the context of computer science education, the learning materials and methodologies employed must be closely aligned with the core competencies required in the field. The chosen journal article for this study was selected based on its ability to challenge the students' understanding and application of complex computer science concepts, thus catering to the development of both technical and soft skills essential for their professional growth. The complexity of the article requires students to employ critical thinking to dissect and understand advanced topics, encouraging the use of algorithmic processes and data analysis techniques that are foundational to computer science. Furthermore, by navigating through the article's challenging content with the aid of generative AI tools, students are able to enhance their problem-solving skills, learning to apply theoretical knowledge to analyze and propose solutions to real-world problems—a key competency in computer science education. Moreover, the framework's structured approach to using AI tools for generating insights and structuring responses also aids in refining students' technical writing and communication skills. These are crucial for articulating technical information clearly and effectively, an essential skill for any computer scientist. The integration of AI tools in this learning process not only supports technical skill enhancement but also fosters the development of critical soft skills such as adaptability, analytical thinking, and the evaluation of technological impacts.

The results presented demonstrate the potential for generative AI writing aids to enhance students' thinking skills and learning outcomes, consistent with the goals of outcome-based education models. By scaffolding responses to higher levels along Bloom's taxonomy, the AI tools based on the proposed framework seemingly enabled more sophisticated conceptualization, evaluation, and synthesis abilities compared to unaided work. Rather than just applying surface-level knowledge, interfacing with the aids facilitated meaningful connections across concepts and the integration of ideas. The interactive nature of the AI workflow has encouraged students to solidify their understanding throughout the writing process actively. Providing samples and templates for integrating information has also guided students to build well-structured, cohesive responses. The GAI has further augmented critical thinking by posing probing questions that pushed students to justify their assertions. All these generative writing scaffolds deepen comprehension and perspective-taking beyond what students could achieve individually. The demonstrated ability of this GAI-powered approach to enhance higher-order cognition and skill application fulfils the core tenets of outcome-based education. The proposed learning framework prioritizes tangible improvements in students' abilities to think critically, problem-solve effectively, and construct new knowledge.

7. Conclusion

This research presented an innovative 6-stage framework for integrating generative AI tools to achieve learning outcomes. The efficacy was tested through an empirical study situating Bloom's taxonomy as the benchmark for quantifiable cognitive enhancements. The investigation uncovered promising evidence regarding generative writing, which aids in enabling students to demonstrate more sophisticated evaluation, synthesis, and analysis aptitudes as measured by elevated Bloom's rubric scores from predominant comprehension and application levels to top-tier skills after structured AI incorporation activities.

The study demonstrated a clear, evidence-based link between the structured integration of generative AI tools and the enhancement of students' cognitive skills. The survey results revealed significant improvements in critical thinking, analysis, and synthesis abilities when students used the ACE Framework, as evidenced by their higher scores on Bloom's taxonomy rubrics. Specifically, students' average thinking level increased from 3.35 (Application) in the unaided phase to 4.85 (Synthesis) in the AI-assisted phase, showcasing the framework's effectiveness in promoting higher-order cognitive skills. The increase in students reaching the highest levels of cognitive ability, such as Synthesis and Evaluation, further supports the claim that the ACE Framework successfully facilitates outcome-based learning. The framework's ability to scaffold student engagement with complex content and generate meaningful insights highlights its potential as a valuable tool for enhancing educational outcomes. These findings provide strong justification for the ACE Framework's role in supporting students in reaching more advanced cognitive levels through structured AI integration.

While this study provides preliminary insights into the integration of generative AI tools in education, we acknowledge the potential for bias in interpreting the results due to the limited sample size and homogeneous student group. To build on these findings, future research should involve larger and more diverse cohorts to enhance the generalizability of the results and to explore the differential impacts of AI tools across various educational contexts. Additionally, longitudinal studies could offer deeper insights into the sustained effects of AI-assisted learning on student outcomes.

At the same time, as an initial investigation, the insights remain bounded by limitations like small sample sizes of 20 students, where future work should incorporate larger, more diverse cohorts. Additionally, relying solely on open-ended written assessments has intrinsic constraints versus evaluating multifaceted skill development through alternative techniques. Creating additional rigour by standardizing AI tools used, controlling prompt formulations, tracking individual progression over longer time spans, and running comparisons to multiple human-only baselines can further refine the understanding of the most impactful scaffolding mechanisms. Nonetheless, this pioneering study establishes an outcomes-focused methodology for harnessing emergent technologies to potentially enrich higher-order cognition, laying the groundwork for further refinements and additional empirical tests to uncover generalizable, ethical AI integration strategies for advancing pedagogical goals targeting sophisticated human-like thinking and comprehension abilities.

Declaration on generative AI: The authors declare that they have not used AI tools in the writing of this article.

Data availability statement: There was no recording or disclosure of any participant's personal information.

Conflicts of interest: The authors declare no conflict of interest.

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