

Assessing the Academic Impact of Generative AI in Higher Education: Student Perceptions and Program Outcome Attainment

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Abstract

Goal: This study investigates the pedagogical impact of integrating Generative Artificial Intelligence (GenAI) into design and engineering education, focusing on student perceptions, academic outcome attainment, and anxiety reduction during skill acquisition.

Design/Methodology: Utilizing an Outcome-Based Education (OBE) model, we mapped hands-on sketching activities utilizing AI-generated visual scaffolding to Program Outcomes (POs). Attainment levels were evaluated using a weighted combination of direct academic performance (80%) and indirect student surveys (20%). Qualitative thematic analysis was applied to student reflections.

Results: Quantitative evaluation showed high Program Outcome attainment, specifically in engineering knowledge and modern tool usage (Level 3, >80%). Students reported significant reductions in anxiety (“blank page syndrome”) and enhanced learning autonomy.

Contribution: This study provides empirical evidence of the value of GenAI as a structured educational scaffolding rather than a copy tool, establishing a roadmap for outcome-driven AI integration in higher education.

Keywords: Generative AI (GenAI), Outcome-Based Education (OBE), Program Outcomes (POs), Educational Assessment, Self-Determination Theory, Drawing Anxiety.

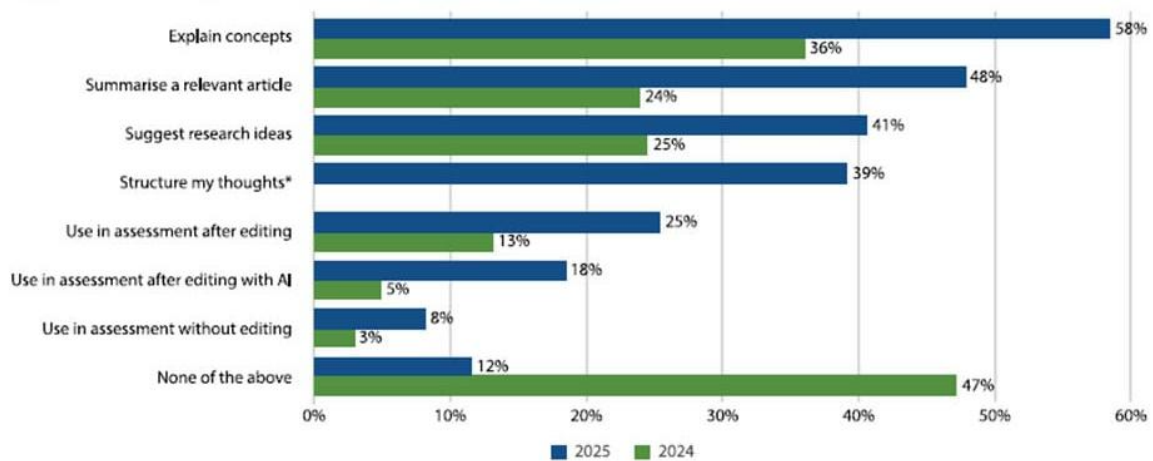
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I. INTRODUCTION

A. AI in Higher Education and Global Student Trends

The rise of Generative Artificial Intelligence (GenAI) has transformed the higher education landscape, shifting technology from a passive administrative tool to an active agent in pedagogy [1]. GenAI tools are increasingly integrated into daily student study routines. According to international indexes, such as the HEPI survey (Figure 1), students are shifting from using AI for basic text generation to using it as a “structured learning assistant.” This is particularly relevant in skill-based and interdisciplinary disciplines, where GenAI bridges the gap between theory and practice [2]. However, this shift is accompanied by discussions regarding academic integrity, algorithmic dependency, and the risk of reducing critical thinking if students become overly dependent on technology [1].



'When thinking about using generative AI to prepare assessed work, which of the following have you ever done? Please select all that apply.'
 * indicates the option is new in 2025. Those putting 'I don't know' (1% of responses in 2025) are excluded

Figure 1: Comprehensive overview of student perceptions regarding the utility of GenAI in higher education (HEPI Student Generative AI Survey 2025 [3]).

B. Pedagogical Challenges and Cognitive Barriers

Learning technical sketching and visual-spatial reasoning—cornerstones of mechanical drawing, CAD, and design thinking—remains a major cognitive hurdle for engineering beginners. Traditional teaching methods often overwhelm novices with complex visual details (textures, lighting, shadows), causing high cognitive load [4]. This overload frequently results in “blank page syndrome” and increased anxiety, which lowers student motivation. In response, educators are exploring visual scaffolding techniques. While AI-generated guide sketches have been proposed to simplify visual data, empirical studies tracking the actual educational outcomes, student perceptions, and Program Outcome (PO) attainment of these methods remain scarce [5].

C. Objectives of the Study

To address the lack of empirical evidence regarding GenAI integration, this paper focuses on: 1. Outcome-Based Mapping: Aligning AI-assisted sketching activities with institutional Program Outcomes (POs) [2]. 2. Quantitative Attainment Evaluation: Measuring the attainment of POs using a direct/indirect weighted assessment framework. 3. Student Perception and Experience Analysis: Assessing student satisfaction, usability, and the reduction of cognitive barriers (drawing anxiety) through survey instruments and qualitative reflections [6].

II. LITERATURE REVIEW

A. Theoretical Pedagogical Scaffold

To evaluate the impact of GenAI on student motivation and learning behavior, this study is grounded in two learning theories: 1. Self-Determination Theory (SDT): SDT posits that intrinsic motivation is driven by three basic psychological needs: autonomy, competence, and relatedness. Using GenAI to generate personalized reference guides increases learning autonomy. Furthermore, immediate visual feedback from AI models reinforces competence as students quickly identify and correct spatial proportion errors. 2. Cognitive Load Theory: A key challenge for novice sketchers is processing too much visual information simultaneously. Providing a simplified visual “giàn giáo” (scaffolding) through AI reduces cognitive load by filtering out unnecessary details, allowing students to focus on core visual-spatial proportions [4].

B. Outcome-Based Education (OBE) in Technology Curricula

Outcome-Based Education (OBE) focuses on measuring student performance through defined Program Outcomes (POs) rather than input hours. In engineering and technology education, integrating new tools (such as drones, CAD software, or GenAI) must show a direct contribution to core competencies, such as technical knowledge (PO1), problem solving (PO3), and modern tool usage (PO5) [2]. While technology adoption generally correlates with higher modern tool usage scores, assessing its impact on design creativity (PO3) and self-reflection (PO10) requires rigorous empirical validation.

III. METHODOLOGY

This study employs a mixed-methods empirical approach, integrating the GenAI framework into an undergraduate computer and electronics engineering graphics curriculum.

A. Mapping Activities to Program Outcomes (POs)

The hands-on educational activities using AI-generated guide outlines are mapped to core Program Outcomes (POs) [2].

TABLE I: MAPPING OF EDUCATIONAL ACTIVITIES TO PROGRAM OUTCOMES (POS)

Educational Activity	Target Program Outcomes (POs)	Pedagogical Role
Analyzing reference image composition	PO1: Technical Knowledge	Understanding visual form, scale, and proportion principles
Interacting with the GenAI tool	PO5: Modern Tool Usage	Mastering AI tools within technical workflows
Sketching based on AI outlines	PO3: Design/Development of Solutions	Translating machine-assisted outlines into freehand drawing skills
Self-reflection and peer feedback	PO10: Communication & Reflection	Internalizing the creative process and learning journey

B. Classroom Implementation and Survey Instrument

Students selected reference images from WikiArt (Landscape, Portrait, Still Life) [7] and processed them using a Stable Diffusion + ControlNet Google Colab notebook [8] to generate simplified guide outlines. Students then hand-drew these outlines, focusing on rendering and shading. Figure 2 illustrates the three distinct stages of this classroom scaffolding process, showing the original input, the AI-generated outline, and the simulated final hand-drawn work.

At the end of the program, students completed a survey using a 5-point Likert scale [6] mapping to the POs (Table II).

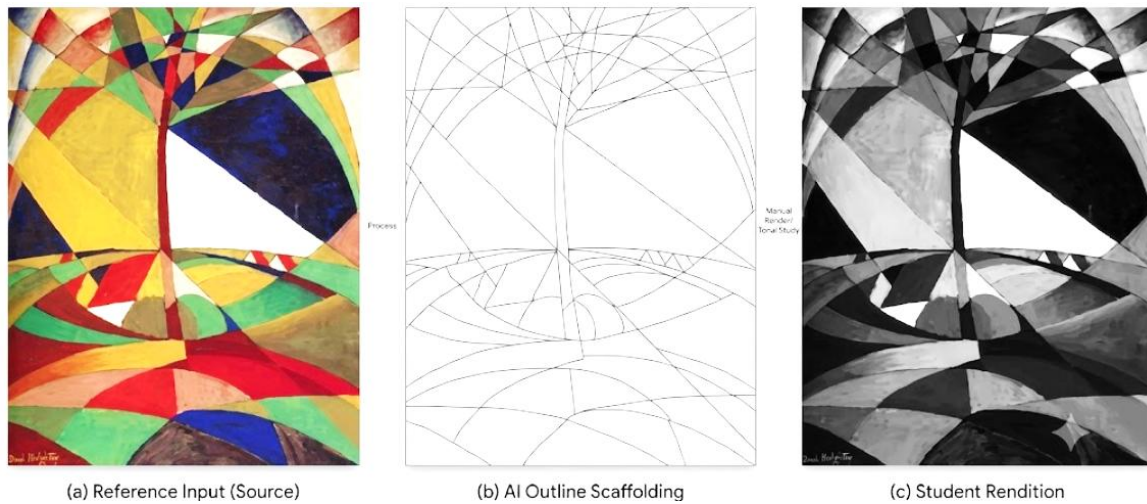


Figure 2: Visual Scaffolding Loop: From reference input, through AI outline scaffolding, to manual student rendition.

TABLE II: SURVEY QUESTIONNAIRE ITEMS AND MAPPED POS

ID	Survey Questionnaire Items	Scale	Mapped POs
1	The AI-generated outline made it easier to identify the layout of complex reference images.	1-5	PO1
2	The visual simplification helped me focus on basic forms without getting distracted by surface details.	1-5	PO1
3	Using the AI guide sketch reduced my anxiety when starting a new drawing (overcoming “blank page syndrome”).	1-5	PO3
4	I felt more confident sketching complex subjects due to the structural scaffolding provided by the AI.	1-5	PO3
5	The Stable Diffusion and ControlNet pipeline was easy to use and integrate into my drawing routine.	1-5	PO5
6	I am satisfied with the AI’s ability to maintain spatial proportions relative to the original image.	1-5	PO5
7	Overall, this AI-assisted learning method is more effective than traditional sketching methods.	1-5	-

C. PO Attainment Calculation Framework

To ensure objective evaluation, overall Program Outcome attainment was calculated using a weighted combination of direct and indirect metrics: * Direct Attainment (80% weight): Based on the evaluation of practical drawing assignments and final projects by an expert panel. * Indirect Attainment (20% weight): Extracted from student self-assessment surveys (Table II).

IV. RESULTS AND DISCUSSION

A. Program Outcome (PO) Attainment Analysis

The weighted attainment calculations for the target Program Outcomes (POs) are summarized in Table III.

TABLE III: SUMMARY OF PROGRAM OUTCOME (PO) ATTAINMENT

Program Outcomes (POs)	Direct Attainment (80%)	Indirect Attainment (20%)	Overall Attainment
PO1: Technical Sketching Knowledge	Level 3	Level 3	Level 3 (High)
PO3: Composition Design & Solutions	Level 2	Level 3	Level 2.2 (Medium)
PO5: Modern Tool Usage (AI)	Level 3	Level 3	Level 3 (High)
PO10: Communication & Reflection	Level 2	Level 3	Level 2.2 (Medium)

The results show high attainment (Level 3, > 80%) for PO1 (Technical Sketching Knowledge) and PO5 (Modern Tool Usage). Direct assessment confirmed that students drew more accurate proportions when utilizing AI outlines. The high PO5 score reflects students’ proficiency in integrating Google Colab, Stable Diffusion, and ControlNet into their learning workflows, matching findings from technology-integration studies [2].

Outcomes for PO3 (Design & Solutions) and PO10 (Communication & Reflection) reached Level 2.2, showing improvement but leaving room for growth. While students designed compositions using AI, translating these digital guidelines into personalized freehand drawings remains a skill that requires additional practice. For PO10, indirect assessment (Level 3) was higher than direct assessment (Level 2), indicating that while students were enthusiastic about discussing AI, their formal technical reflection reports require further academic development.

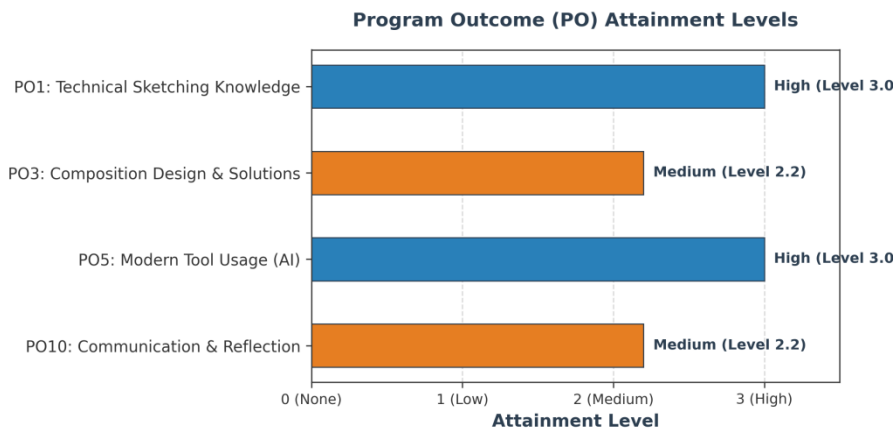


Figure 3: Student Program Outcome (PO) attainment levels.

B. Student Survey Feedback and Reliability

Internal consistency checks confirmed survey reliability. Cronbach’s Alpha for satisfaction and utility item groups exceeded 0.80, meeting the accepted threshold for educational research [6]. Furthermore, positive feedback (with 81.75% rating the tool as “Very Good” or “Excellent”) suggests that cognitive load reduction positively influenced student motivation (Figure 4).

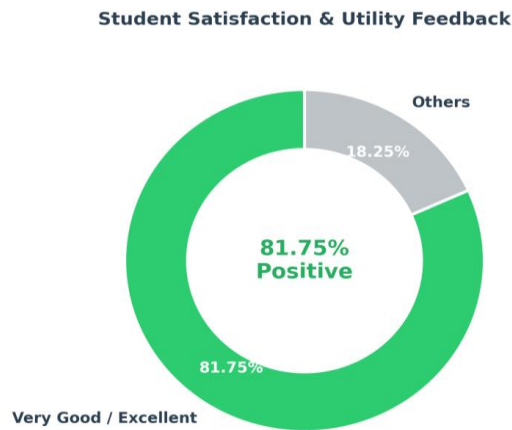


Figure 4: Distribution of learner feedback regarding pedagogical utility and satisfaction.

C. Qualitative Reflections and Student Experience

Thematic coding of students' open-ended responses identified three primary benefits: 1. Autonomy and Agency: Students reported feeling in control of their learning pace ("I felt in charge of my sketching workflow and could adjust my learning speed autonomously"). 2. Adaptive Feedback: The AI acted as a visual guide, offering reference prompts when students struggled with layout proportions. Feedback distribution (Figure 4) indicates that the AI tool helped reduce drawing anxiety. 3. Mitigating Blank Page Syndrome: The tool lowered initial anxiety when starting complex drawings, allowing students to experiment with rendering style and shading more confidently (Figure 3).

V. CONCLUSION AND FUTURE DIRECTIONS

A. Conclusion

This study empirically validated a pedagogical framework using Generative AI to support sketching instruction in engineering graphics education. Utilizing an outcome-based model, we demonstrated that AI-generated outlines serve as an effective scaffolding tool, helping students achieve core competencies in technical knowledge (PO1) and modern tool usage (PO5) [2]. The visual simplification significantly reduced drawing anxiety, allowing students to focus on creative rendering while maintaining proportion accuracy.

B. Future Research Directions

To expand upon these results, future work should address the following areas: 1. Assess Long-Term Skill Retention: Conduct longitudinal studies to track whether skills developed using AI support successfully transfer to independent, unassisted drafting tasks after graduation [2]. 2. Expand Sample Size and Diversity: Test the framework across different demographic groups and engineering disciplines (e.g. civil and mechanical engineering) to evaluate generalizability. 3. Develop Institutional Policies: Establish guidelines regarding responsible AI usage, data privacy, and academic integrity to ensure sustainable educational practices [1].

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