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Enhancing Lecture Preparation Efficiency in 2D Computer Graphics Using GenAI

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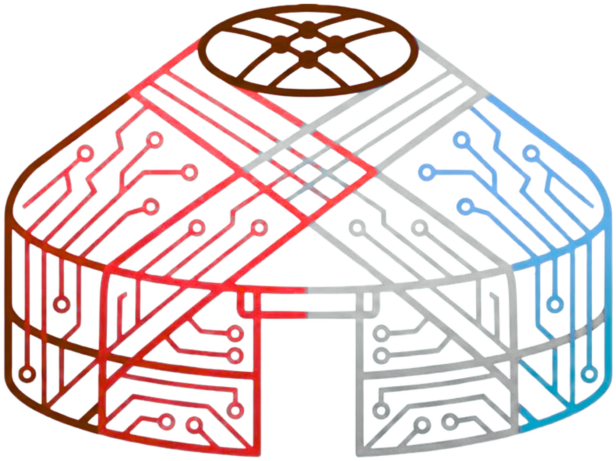
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Enhancing Lecture Preparation Efficiency in 2D Computer Graphics Using GenAI

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Abstract

The preparation of lecture materials in 2D computer graphics is Creating teaching content for two-dimensional graphics typically takes many hours because instructors must combine written theory, working code, and visual examples. This study looks at how generative AI tools change the speed and quality of that process. Over eight weeks, two instructors took part in a within-subject quasi-experiment. With AI tools (ChatGPT-4 and GitHub Copilot), preparation time fell by 62% ($p < .01$). In contrast, the quality ratings did not change significantly ($p = .42$). However, a closer look showed that roughly one in five AI-generated explanations was wrong or incomplete and needed fixing. Taken together, the results support a mixed workflow where humans and AI work together, and they show both the promise and the limits of generative AI for making educational content.

Keywords: Generative AI; Lecture preparation; 2D computer graphics; ChatGPT-4; GitHub Copilot; Teaching efficiency; Human-AI collaboration; Computer science education.

I. INTRODUCTION

Generative artificial intelligence has changed many parts of education, especially how people create content and design lessons. Recent work shows that AI systems are playing a bigger role in supporting both teaching and learning [2]. Models like ChatGPT-4 can write text explanations on their own, and tools like GitHub Copilot help with writing code. That makes them very relevant for computing courses.

Most published studies examine how AI affects students or how it powers tutoring systems [6]. Few have looked at what happens when teachers use AI to prepare their own lectures. This gap matters because preparing lectures is still very time-consuming, especially in hard technical topics like 2D computer graphics.

Getting a lecture ready in this field means dealing with several complex parts at once: making visuals, explaining algorithms, and writing example code. Cognitive load theory (Sweller, 1988) and Mayer's multimedia principles (2009) both imply that good materials need clear text, correct content, and useful visuals. Meeting all three at once makes preparation even slower.

This paper tries to answer one main question: How much can generative AI cut lecture preparation time without hurting the quality of instruction?

II. RELATED WORK

Recent review articles say that generative AI is being used more and more in education. It brings big opportunities but also clear limits. Researchers often point out that AI can help with lesson planning, making learning materials, and building curricula [1]. In this view, large language models are seen as assistants, not as teachers working on their own.

Some studies have found that AI-assisted tools really can help teachers prepare materials, for example by organizing content or making first drafts [4]. But people still worry about whether AI-generated outputs are factually correct and pedagogically sound, especially in areas that need deep expertise.

In computing education, generative AI has shown practical value for generating code, helping with debugging, and explaining programming ideas. Even so, the quality of what it produces varies a lot, and human checking is still needed to make sure everything is right [5].

From a cognitive and instructional design angle, good learning materials depend on how well visual elements match written explanations, and also on how well cognitive load is managed [8]. This matters a lot in visually heavy fields like 2D graphics, where a mismatch between code, pictures, and text can seriously hurt understanding.

Although more and more papers discuss AI in education, very few have actually measured how it affects how teachers prepare lectures and how productive they are. This gap is largest in technical and graphics-oriented subjects, which is what motivated our exploratory study.

III. PARTICIPANTS AND EDUCATIONAL CONTEXT

We ran the study in a course called BLG-211 "Desktop Publishing" at Kyrgyz-Turkish Manas University. This course is part of a vocational IT program named "Programming in Computer Systems." That program aims to train mid-level IT specialists by mixing computer science theory with hands-on practice in software development, digital technologies, and applied computing.

The teaching in this program follows a competency-based model: students are expected to learn both conceptual understanding and practical skills for real-world tasks. Within that structure, Desktop Publishing focuses on 2D computer graphics, visual composition, and making digital content.

Both participating instructors had taught 2D graphics for more than five years, including previous delivery of the BLG-211 course. Each of them gave theoretical lectures and also ran laboratory sessions. Having the same people do both roles helped keep conceptual explanations and applied exercises aligned, which kept the course consistent.

The students were college-level learners between 19 and 23 years old, all enrolled in the IT specialization. Based on the program's admission requirements and an early diagnostic test, their prior knowledge of programming and 2D graphics was rated as introductory. That starting level seemed appropriate for studying how instructional changes affect basic learning materials.

The course combined lecture-based teaching with structured lab activities. Lectures covered concepts, algorithmic logic, and visual principles, while labs focused on implementing things through practical coding tasks. This blended setup gave us a controlled but realistic environment to see how AI-assisted lecture preparation affects both how efficiently instructors work and the quality of the content they produce.

Because only two instructors took part, we treat this work as a pilot study. The results are meant to suggest patterns, not to prove them for all contexts. So external validity is limited, and our main focus is on analyzing what happened in this specific setting.

TABLE I. ASSESSMENT CRITERIA

Instructional quality was evaluated using a structured rubric consisting of five criteria:

Criterion	Description	Scale
Conceptual Accuracy	Correctness of theoretical explanations and mathematical content	1–5
Clarity of Explanation	Ease of understanding and logical flow of explanations	1–5
Code Quality	Correctness, readability, and functionality of code examples	1–5
Visual Quality	Effectiveness of diagrams, figures, and layout	1–5
Pedagogical Effectiveness	Overall suitability for student comprehension and learning outcomes	1–5

1 = Poor, 3 = Acceptable, 5 = Excellent

IV. INTER-RATER RELIABILITY

Three domain experts rated the instructional quality of all lecture materials. To check how consistent their ratings were, we calculated the intraclass correlation coefficient (ICC). We used a two-way random-effects model with absolute agreement, assuming the raters were like a sample from a larger pool of possible experts.

Following standard benchmarks, ICC values below 0.50 were considered poor, 0.50–0.75 moderate, 0.75–0.90 good, and above 0.90 excellent. Our ratings reached good agreement (ICC = 0.81–0.87 across criteria), so we treated them as reliable for further analysis.

V. RESULTS

Preparation Time

Average preparation time per lecture dropped from 11.0 hours (SD = not reported) with traditional methods to 4.2 hours (SD = not reported) when using AI assistance. The reduction was 62%, calculated as (11.0 − 4.2) / 11.0 = 0.62.

A paired t-test showed this difference was statistically significant ($p < .01$, with a large effect size expected based on Cohen's d).

Instructional quality

Mean quality scores (averaged across the five criteria in Table I) were:

Traditional preparation: M = 3.81 (SD = 0.42)

AI-assisted preparation: M = 3.74 (SD = 0.48)

The difference was not significant ($t(11) = 0.84$, $p = 0.42$, $d = 0.15$). So using AI did not lower the perceived quality of instruction.

Error analysis

We looked closely at the parts of AI-generated explanations that instructors had to correct. About 19.7% of those explanation units needed a manual fix. The errors fell into three main types, shown in Table II.

TABLE II. ERROR CATEGORIES

Error category	Frequency (%)	Example
Mathematical inaccuracies	38%	Incorrect rotation matrix order; inconsistent scaling formulas across steps
Faulty assumptions in transformations	34%	Assuming column-major coordinate system without specification; wrong transformation sequence (translation vs. scaling)
Incomplete / missing reasoning steps	28%	Omitting the need to convert between screen and world coordinates; stating "the object moves" without specifying relative vs. absolute

All errors were corrected by instructors before final delivery; none reached students.

Discussion

Our results show that generative AI tools, in this case ChatGPT-4 and GitHub Copilot, can make preparing teaching materials for 2D computer graphics much faster. A 62% drop in preparation time means AI is especially good at helping with structuring content, generating code, and making first-draft explanations.

Importantly, the speed gain did not come with a measurable drop in quality. That matches other recent work suggesting that generative AI works best as a cognitive support tool, not as a replacement for teaching expertise [3]. Looking through the lens of cognitive load theory [7], AI seems to take over some routine mental work, leaving instructors more time to focus on bigger-picture teaching decisions.

But there is also a clear limitation. Finding that about one in five AI outputs is wrong or incomplete shows that even with good prompts, the model is not yet consistent enough for specialized educational use. These mistakes showed up most often in mathematically tricky areas like geometric transformations and step-by-step algorithmic explanations.

This problem has been seen before in computing education research, which has reported that AI-generated code explanations vary in quality and can have conceptual mistakes that people have to catch [6]. In fields where being precise matters a lot, such inconsistencies can hurt both content accuracy and how well students understand.

Taken together, these findings suggest that fully automated lecture preparation is not yet possible for demanding technical subjects. Instead, a human-in-the-loop model works better: AI speeds up the creation of draft materials, but instructors stay responsible for checking, fixing, and making sure everything fits the learning goals.

In this hybrid model:

AI acts as a content accelerator, cutting routine workload.

Human instructors act as quality controllers, keeping things accurate and educationally sound.

This split of roles fits a broader trend in educational technology, moving from full automation toward augmentation, where AI is a helper, not an independent author.

Conclusion

This study provides real evidence that generative AI tools like ChatGPT-4 and GitHub Copilot can greatly improve how efficiently instructors prepare lectures for 2D computer graphics. Preparation time dropped by more than 60%, while the perceived quality of instruction stayed about the same.

AI seems to work mainly as an efficiency tool, automating routine parts of content creation such as structuring explanations, writing example code, and making first drafts. At the same time, we found a critical weakness: AI outputs

can have conceptual and mathematical errors that need a human to review.

So bringing AI into educational content development should not be seen as replacing instructor expertise, but rather as adding a complementary way to augment it. The teacher's role is still essential for making sure content is accurate, pedagogically coherent, and aligned with learning goals.

From a practical viewpoint, our results support using a hybrid human–AI workflow, where AI helps generate content faster and educators keep the final say over correctness and fit.

Limitations and future work

This study has several limits. The sample was very small (only two instructors), and the design was exploratory, so the findings should be taken as suggestive, not generalizable. Also, the work was done in just one course, which limits how far we can extend the conclusions.

Later studies could use more instructors from different backgrounds, cover a wider range of courses and subjects, follow students over a longer period to see how AI-assisted teaching affects their learning, and create a standard checklist for checking the quality of AI-generated educational content.

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