Case Study on Llama-Based AI Tutors for Computer Science Education in Remote Areas

Abstract

In remote and underserved locations, there is a serious education crisis because of the low number of trained educators and learning opportunities to provide quality computer science instruction. The present case study focuses on the way that Llama-based AI tutors impacted more than 370 students with the help of hybrid learning, showing considerable advances in the solving of assignments and the improvements of the learning outcomes. The research is based on the theory of Zone of Proximal Development introduced by Vygotsky and investigates the influence of AI-based instructional support on the scope of knowledge and developing inclusive learning patterns. These results are supported by quantitative data and qualitative feedback, which shows that AI tutors have the ability to maximize student engagement and performance as well as areas of improvement. The results are crucial in the understanding of the transformative nature of AI in the education process and human-AI partnership in the classroom.

1. Introduction

Our knowledge-based economy has created a necessity to have access to quality Computer Science (CS) education. The skills of computational thinking, programming, and digital literacy are the markers of not only STEM career readiness but also a prerequisite of valuable engagement in the digital economy. Nonetheless, there remain serious disparities in CS education opportunities particularly to students in remote, rural or deprived regions where schools lack structural or human capital inadequacies.

This gap has a direct effect on Sustainable Development Goal 4 (Quality Education) and SDG 10 (Reduced Inequalities) because of which educational solutions are needed now more than ever. Most of the schools in these regions face extreme lack of sufficient trained teachers, poor student to teacher ratios, and exposure to technological trends. Further, this is compounded by poor internet connection, lack of equipment and lack of extracurricular educational facilities.

One of the possible solutions to provide equal access to quality teaching through democratization is Artificial Intelligence (AI) driven educational technologies. The research outlines a practical case study of the implementation and evaluation of an AI tutor based on LLaMA in hybrid educational settings that involves 370+ students and focuses on quantitative performance and qualitative experience.

This paper presents a real-world case study on the deployment and assessment of a LLaMA-based AI tutor to support computer science education across a diverse cohort of over 370 students, including more than 240 online participants and over 130 in-person learners. The study was conducted in a hybrid learning environment where:

In-person students had access to both human instructors and the AI tutor, fostering blended interaction.

Online students who were geographically distributed were mostly involved with the AI tutor as the primary provider of instructional support systems.

The AI tutor was designed to provide automated explanations to topics, help in assignment solving work and provide real-time feedback with the aim of enhancing learning while eliminating the effects of limited instructor time.

In order to assess the efficiency of the AI-based intervention, the conducted study applied mixed-methods approach, involving:

- Quantitative performance indicators (i.e.: assessments and problem-solving ability),
- Usage and engagement data (counting the interaction length and time)
- Qualitative feedback from students and instructors (collected using surveys/interviews).

The findings show that AI-backed learning resulted in significant improvement in students' performance as compared to their counterparts who normally use the traditional self-learning approaches; there was 25% average growth in assignment solving and problem solving skills. In addition, the hybrid model became one of the very effective pedagogical strategies that combined the effectiveness and availability of AI with the knowledge and empathy of human teachers.

This case study not only advances AI-enabled education, but also offers actionable insights into deploying such systems in low-resource circumstances, namely, content accuracy, equity of access, and adaptive learning.

By this, it sets the ground for the development and policy frameworks that will guide towards the generation of inclusive and high-quality CS education through human-AI collaboration in settings where traditional education remains lacking.

2. Theoretical Framework

The research is based on the theory of Zone of Proximal Development (ZPD) by **Vygotsky** who states that the learning process is most effective when a student is provided with the necessary scaffolding to fill the gap between the actual and the possible development. ZPD framework is especially applicable to the AI tutoring systems due to the following reasons:

1. **Scaffolding Support**: AI tutors can provide immediate, contextual assistance that helps students work through problems just beyond their current competence level.

2. **Personalized Guidance**: The AI system can adapt explanations and hint levels based on individual student responses, maintaining optimal challenge levels.

3. **Human-AI Collaboration**: The hybrid model leverages human instructors for complex conceptual guidance while AI provides consistent, available support for routine technical questions.

Constructivist Learning Theory is also applied in the study and knowledge is developed actively by interaction with the learning materials as well as peers. It is made possible by the AI tutor which offers instant feedback, promotes iterative problem-solving and allows students to develop their understanding through exploration.

3. Literature Review

3.1 AI in Education: Current Landscape

In the recent past, there have been notable developments in the AI tutoring systems which have shown to be of great value in education. In controlled studies, Kulik and Fletcher (2016) discovered that intelligent tutoring systems yield

learning gains that are similar to those created by human tutoring. In the same way, a study by Ma et al. (2021) showed that AI chatbots in classrooms enhanced the engagement of students by 34 percent in comparison to the conventional online learning interfaces.

The use of AI systems in teaching computer science in particular has been promising. Chen et al. (2020) applied AI coding assistant to students of programming courses and recorded a 40 percent decrease in their debugging time. Nonetheless, the majority of the research has been done in well-resourced settings, which creates a big research gap on the effectiveness of AI tutoring in resource-strained and distance learning settings.

3.2 Research Gap

While existing literature demonstrates AI tutoring potential, several gaps remain:

1. **Geographic Context**: Limited studies examine AI tutoring in remote, underserved regions with infrastructure constraints.
2. **Hybrid Learning Models**: Insufficient research on optimal human-AI collaboration in educational settings.
3. **Scalability**: Few studies address large-scale deployment (300+ students) across diverse learning environments.
4. **Long-term Impact**: Most studies focus on short-term outcomes rather than sustained learning improvements.

3.3 AI Ethics in Education

There are some important ethical questions about AI in education. The issue of data privacy ranks top among the concerns especially when the student interaction data is to be used on the system improvement (Rowe & Lester, 2015). Educational disparities may continue to exist because of the bias of algorithms when AI systems are trained using non-representative data (Baker & Hawn, 2022).

Consent and transparency are the areas of concern when students communicate with AI systems without complete knowledge about data use. Also, the issues of surveillance are introduced by constant student interaction monitoring, leading to the development of digital supervision-like environments instead of positive learning conditions (Prinsloo & Slade, 2017).

3.4 Equity and Inclusion in Remote Learning

The digital divide has a severe effect on remote learning educational equity. According to Reich & Mehta (2020), the engagement level of low-income students was 30 percent lower than that of the advantaged students in online learning settings.

The issues of language barrier, cultural relevance, and accessibility to technology are also major problems to the inclusive AI educational systems.

4. Methodology

4.1 Research Design

The research design of this paper was **mixed-methods** that use both **quantitative** performance measures and **qualitative** analysis of feedback. The methodology allowed the assessment of AI tutor performance in a wide range of learning situations and students.

4.2 Participants and Sampling Strategy

Total participants: 370 students

- **In-person cohort**: 130 students (regional educational center)
- **Online cohort**: 240+ students (distributed remote learning)

Sampling Strategy: Convenience sampling was employed due to accessibility constraints in remote areas.
Demographics:

- Age range: 18-28 years
- Academic levels: 60% undergraduate, 40% post-graduate
- Geographic distribution: 15 different regions across rural and semi-urban areas
- Technology familiarity: Basic to intermediate digital tool usage

Inclusion Criteria: Students enrolled in computer science or related programs with basic English comprehension.
Exclusion Criteria: Students without reliable internet access for online participation.

4.3 AI Tutor System Design

The LLaMA-based AI tutor was fine-tuned on curated Virtualization and Cloud Computing curricula, including:

- Virtualization concepts and implementation
- Cloud computing architectures and services
- Distributed systems fundamentals
- Container technologies and Docker

Technical Implementation: The system was deployed using a scalable cloud architecture with the following components:

- **Frontend**: Web-based interface with mobile responsiveness
- **Backend**: LLaMA model integration with vector database for context retrieval
- **Data Collection**: Interaction logging system for usage analytics
- **Security**: End-to-end encryption and anonymized data storage

4.4 Learning Model Implementation

Hybrid Learning Framework:

- **In-person students**: Access to both human instructors and AI tutor for blended interaction
- **Online students**: Primary engagement with AI tutor, supplemented by weekly virtual sessions with human facilitators

Controls and Limitations: There was no classical control group since the study presented an ethical dilemma of not providing any educational assistance to students living in underserved regions. Rather, the performance was compared to those of the past students and the self-reported experiences of conventional studies.

4.5 Data Collection and Analysis

Quantitative Measures:

- Pre/post assessments on core CS concepts
- Assignment completion rates and accuracy scores
- Engagement metrics (interaction frequency, session duration)
- Problem-solving performance indicators

Qualitative Measures:

- Student feedback surveys (n=300+ responses)
- Instructor interviews (n=8 participants)
- Learning reflection journals (optional, n=120 participants)

Data Analysis: Quantitative data was analyzed using descriptive statistics and paired t-tests for pre/post comparisons. Qualitative data underwent thematic analysis using open coding techniques to identify recurring patterns and themes.

5. Results and Analysis

5.1 Learning Outcomes [ENHANCED WITH VISUALS]

Table 1: Performance Improvements by Cohort

Metric	In-Person Students	Online Students	Overall
Assignment Accuracy	+28%	+23%	+25%
Problem-Solving Speed	+32%	+19%	+24%
Conceptual Understanding	+35%	+22%	+27%
Code Debugging Skills	+40%	+25%	+31%

Statistical analysis revealed significant improvements across all metrics ($p < 0.001$, paired t-test). The AI tutor demonstrated particular effectiveness in debugging assistance and step-by-step problem-solving guidance.

The incorporation of the LLaMA-based AI tutor into a hybrid learning paradigm led to results that could be quantified in terms of enhanced learning results obtained by the student, especially in problem-solving and assignment solving proficiency. Compared with students who only made use of traditional self-learning (e.g., static online tutorials, pre-recorded videos, and textbooks), students who interacted with the AI Tutor posted a 25% improvement in formative learning (e.g., assignment challenges and algorithm problem sets). These benefits were similar for both in-person cohorts and those in remote learning who were mostly communicating with the AI system.

In the Virtualization and Cloud Computing (VCC) course at IIT Jodhpur, the AI assistant supported deeper conceptual understanding as explanations were made based on the user's query. As for assignment solving accuracy, the ability to detect logic error, and the documentation clarity, all these improved over the semester. Sequential assignment tracking demonstrated enhanced capability to attack higher-order problems, and thus it helped establish that students were not simply memorizing syntax but learning to adapt to key computational principles.

5.2 Engagement and Usage Patterns

Figure 1: Weekly Interaction Patterns

- Average weekly interaction: 3.7 hours
- Peak usage: Evening hours (6-10 PM)
- Intensive periods: 7+ hours during project deadlines
- Correlation with assignment deadlines: r = 0.78

Usage Distribution:

- Technical syntax queries: 35%
- Conceptual explanations: 28%
- Assignment assistance: 22%
- System design questions: 15%

The interaction logs with the AI tutor indicated high engagements, particularly among the remote learners. Overall, students invested 3.7 hours every week to interact with the AI tutor and more advanced students even interacted for as long as 7 hours when they were in the intense project periods. Utilization densely crowded the week except for evenings during the weekdays, corresponding to independent studies.

Remarkably, the peak usage was highly associated with deadlines of assignments and preparation for exams, indicating that students actively incorporated the AI tutor as part of their workflow in terms of studying. This habit follows the patterns of usage seen in the class bot of the VCC course, where students had been using the AI system for late night study and technical review. The strong alignment of the AI query topics and course context also suggested successful curricular integration with the topics of assignment solving syntax, system design, and cloud models being most prevalent. Temporal analysis also discovered a pattern of recurring interaction sequence where students turn back to AI tutor for clarification, follow-up questions and further exposition of topics- a pattern that supports claims that the system caused progressive learning and iterative problem solving.

5.3 Comparative Analysis

Table 2: Comparison with Other AI Tutoring Systems

Study	System Type	Student Count	Performance Gain	Engagement Rate
Current Study	LLaMA-based	370	+25%	87%

Chen et al. (2020)	Rule-based	150	+18%	72%
Ma et al. (2021)	Chatbot	200	+21%	79%
Kumar et al. (2022)	GPT-based	100	+29%	91%

The current study demonstrates competitive performance gains with significantly larger scale deployment, suggesting good scalability potential.

5.4 Student Feedback Analysis

Positive Responses (n=300+ survey responses):

- **70%** of online students rated explanations as "clear" and "contextually relevant"
- **85%** preferred hybrid learning over AI-only instruction
- **60%** valued 24/7 availability for off-hours learning support

Thematic Analysis Results:

1. **Accessibility**: Students appreciated immediate response availability
2. **Non-judgmental Support**: AI tutor provided safe space for repeated questioning
3. **Consistency**: Reliable quality of explanations across topics
4. **Personalization**: Adaptive response levels based on student queries

Very positive perceptions of the effectiveness of the AI tutor were reported by the students. An analysis carried out on survey replies of more than 300 respondents indicated several key trends:

As regards to the online students, 70% of them declared that the AI tutor's explanations were "clear," "contextually relevant," and "easy to understand". This group highly appreciated the ability of the tutor to give just-in-time assistance, which was especially important in the case of absence of human instructors.

85% of students (regardless of the remote and physical cohorts) preferred hybrid learning environments where AI systems supported rather than replaced human teaching. They used the AI tutor being able to provide an answer to routine or technical questions as allowing the instructors to spend more interesting time, for example, on project feedback or conceptual walkthrough.

60% of students valued the 24-hour availability of an AI tutor especially when it was prompt in responding to them late at night when the traditional support system was unavailable to them. This was very important to working students or those located in countries with a different time zone from the central instruction team.

Qualitative feedback focused on the conversational tone, adaptability in different learning styles, and helpfulness in cases of syntax mistakes or conceptual blunders, of the AI tutor. Students repeatedly referred to the AI tutor as "approachable," "non-judgmental," and "persistent," in comparison to more traditional support structures which may be time-ailing or threatening.

5.5 Staff Impact and Multilingual Accessibility

Instructor Workload Analysis:

- **40% reduction** in routine technical question handling
- **Increased focus** on high-level conceptual guidance and project mentoring
- **Enhanced class dynamics** with more interactive, discussion-based sessions

Language Support Limitations:

- Primary language: English (100% coverage)
- Regional language support: Limited to basic technical terms
- **Challenge identified**: Need for enhanced multilingual capabilities for broader accessibility

Instructors in the pilot study gave a complex picture of the role of the AI tutor in the teaching ecosystem. One of the popular sentiments was that the LLaMA-based system was efficient in relieving instruction burden by responding to repetitive and low complexity questions. These consisted of giving clarifications in syntax, explaining error messages and tracing algorithms – all tasks that once took up a lot of time from the instructor and TAs' schedules.

This automation of interactions enabled educators to shift their attention to more advanced pedagogical work like mentoring student capstone endeavors, guiding the discussions in groups, as well as offering focused concepts' clarification. This change also enhanced class dynamics with human class sessions becoming more interactive and concept-driven.

However, instructors also outlined some of the limitations in the performance by the AI tutor. One such problem was contextual accuracy; while the tutor was brilliant in providing isolated and technical responses, sometimes it had difficulties responding to multi-part or ambiguous queries that would require a situation or the real-world nuance. Besides that, the necessity of human oversight, specifically in the high-stake assessments or emotionally charged situations (e.g., academic stress, plagiarism concerns or the case when specially tailored feedback on grading is given) was highly stressed out where empathetic responses and ethical judgment became crucial.

5.6 Infrastructure and Connectivity Challenges

Digital Divide Impact:

- **23%** of students experienced connectivity issues affecting usage
- **Mobile-first usage**: 65% of interactions occurred on mobile devices
- **Data consumption**: Average 2.5GB monthly per student
- **Offline capability**: Identified as critical need for 30% of student population

6. Discussion

6.1 Theoretical Implications

The study validates Vygotsky's ZPD theory in AI-mediated learning contexts. The AI tutor effectively provided scaffolding support, enabling students to tackle problems beyond their independent capability. The 25% improvement in assignment solving demonstrates how appropriate technological scaffolding can enhance learning outcomes.

Constructivist Learning Evidence: Students' iterative interaction patterns with the AI tutor (average 3.2 follow-up questions per session) indicate active knowledge construction rather than passive information consumption.

6.2 Learner Engagement and Performance Impact

The hybrid learning model turned out to be the most effective one, as 85 percent of students stated that they would rather learn with the help of a human teacher backed by AI rather than learn solely with the help of AI. This observation is in line with the human-in-the-loop learning strategy, in which technology complements instead of substitutes human knowledge.

Long term Impact Considerations: Although this study was able to capture short term performance gains, longitudinal measurement is required to measure retention and the transfer of skills. The similar use trends indicate the lasting engagement, yet the academic performance monitoring after the course completion period would reinforce the impact assertion.

6.3 Transferability and Scalability

Regional Adaptability: The system's effectiveness across 15 different geographic regions suggests good transferability potential. However, cultural and linguistic adaptations would be necessary for global deployment.

Scalability Factors:

- **Technical**: Cloud architecture supported 370+ concurrent users effectively
- **Pedagogical**: Standardized curriculum integration enables replication
- **Economic**: Cost-effective compared to hiring additional qualified instructors

6.4 Comparison with Previous Studies

The results of the study correspond to Chen et al. (2020) in terms of the effectiveness of debugging assistance but show better engagement rates (87% vs. 72%). The bigger scale deployment (370 vs. 150 students) implies that the system is effective at scale, which is one of the limitations of the prior research.

In contrast to the controlled laboratory experiment by Kumar et al. (2022), the study exhibits the applicability of the project to a real-life situation in a resource-limited setting, which makes the research results more ecologically valid.

6.5 Limitations and Challenges

Content Accuracy: The AI tutor performed well, but in some cases it would give partial or otherwise too generic answers to multi-faceted questions. This shortcoming highlights how human supervision is still needed in risky educational situations.

Equity Concerns: The digital divide had a significant effect on participation where 23 percent of students had connectivity concerns. The above finding is an indication that infrastructure disparities need to be addressed together with the implementation of educational technology.

Adaptive Learning Gaps: The system in place did not have long-term learning pathway adaptation memory. The students who needed continuous scaffolding were given the same kind of response as time passed and they did not get gradually increased support.

7. Conclusion and Recommendations

7.1 Study Conclusions

The case study shows that using LLaMA-based AI tutors can help open access to computer science education and improve the quality of remote education drastically. The fact that the performance of solving assignments improved by 25 percent, with the engagement rates of 87 percent and student feedback being positive, underlines the possibility of AI-mediated learning in underserved environments.

Key Findings:

1. **Hybrid learning models** prove most effective, combining AI scalability with human expertise
2. **Significant performance gains** achieved across diverse student populations
3. **Instructor workload optimization** enables focus on high-level pedagogical tasks
4. **Infrastructure challenges** remain significant barriers to equitable access

7.2 Policy and Institutional Recommendations

Policy-Level Recommendations:

1. **Infrastructure Investment**: Governments should prioritize rural internet connectivity and device access programs
2. **Teacher Training**: Integrate AI-literacy training into educator professional development
3. **Ethical Guidelines**: Develop clear frameworks for AI educational tool deployment, addressing privacy and consent
4. **Equity Monitoring**: Establish systems to track and address digital divide impacts

Institutional Recommendations:

1. **Gradual Implementation**: Pilot AI tutoring systems in small cohorts before large-scale deployment
2. **Cultural Adaptation**: Customize AI responses for local languages and educational contexts
3. **Offline Capabilities**: Invest in systems that function in low-connectivity environments
4. **Human-AI Training**: Prepare instructors for collaborative teaching with AI systems

7.3 Alignment with Sustainable Development Goals

This study directly supports:

- **SDG 4 (Quality Education)**: Demonstrates scalable approach to improving educational access and quality
- **SDG 10 (Reduced Inequalities)**: Addresses educational disparities between urban and rural areas
- **SDG 9 (Industry and Innovation)**: Showcases innovative technology application for social good

7.4 Future Research Directions

Immediate Priorities:

1. **Longitudinal Studies**: Track long-term learning retention and skill transfer
2. **Multilingual Development**: Expand language support for diverse populations
3. **Offline System Development**: Create lightweight, edge-deployable versions
4. **Emotional Intelligence Integration**: Develop empathetic response capabilities

Research Questions for Future Investigation:

- How do AI tutoring systems impact different learning styles and cultural contexts?
- What is the optimal balance between AI and human instruction across different subjects?
- How can persistent learning models be developed for long-term educational relationships?

Methodological Improvements: Future research ought to embrace randomized controlled studies where possible, various comparison groups, an advanced use of learning analytics to get a better insight into student learning patterns.

7.5 Final Reflections

The effective implementation of AI tutoring technologies in the learning environment in some of the most difficult situations proves how technology can democratize access to learning. Nevertheless, to achieve this potential, it is necessary to fix the infrastructure inequalities, cultural relevance, and ethical principles. The way ahead requires a synergistic innovation of educators, technologists, and policymakers with a focus on inclusive design and human-AI synergy.

With the priority of equity-driven AI development and sustainable models of AI implementation, intelligent learning environments can grow without limitations and improve the quality of education of all learners, especially those that belong to underserved communities and are the most likely to see these technological innovations as beneficial.