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Educating with AI: Evaluating the Impact of Generative Systems on Student Learning and Engagement

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Abstract

The integration of Artificial Intelligence (AI) into Computer Science (CS) and Information Systems (IS) curricula has accelerated rapidly, offering new opportunities to enhance student engagement, cognitive development, and learning outcomes. In particular, recent advances in Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) have enabled AI-driven tutoring systems that increasingly resemble human tutoring interactions. This study investigates two complementary dimensions of AI adoption in CS education. The first dimension presents a comparative analysis of AI-based tutoring and traditional human tutoring, focusing on learning outcomes, engagement, satisfaction, and instructional explainability. The second dimension examines authentic student–AI interaction data derived from engagements with an LLM-based virtual assistant across multiple CS course assignments. Using a data mining methodology implemented in RapidMiner, the study analyzes performance metrics, behavioral indicators, and interaction patterns to assess learning efficacy and pedagogical impact. The findings indicate that AI tutoring can yield high learning gains and increased engagement, albeit with greater variability, while human tutoring provides more stable outcomes and higher satisfaction. Interaction-level analysis further demonstrates that AI tutors are particularly effective in formative learning contexts and conceptually demanding topics. Collectively, the results support a hybrid instructional model that integrates AI tutoring within human-guided educational frameworks to optimize learning effectiveness and ethical use.

I. Introduction

Artificial Intelligence has emerged as a transformative force in higher education, particularly within Computer Science and engineering disciplines where both the subject matter and pedagogical methods are increasingly intertwined with AI technologies. Educational institutions are exploring AI-driven tools to address challenges such as large class sizes, diverse learner needs, and the demand for personalized instruction. Among these tools, AI-based tutoring systems—especially those powered by Large Language Models—have attracted significant attention for their ability to provide on-demand, conversational, and adaptive learning support. Despite growing adoption, questions remain regarding the comparative effectiveness of AI tutors versus human tutors and the conditions under which AI-driven instruction most effectively supports learning. Moreover, while prior research has largely focused on learning outcomes, fewer studies have examined fine-grained interaction data that reveal how students actually engage with AI tutors during authentic learning tasks. This study addresses these gaps by combining outcome-level and interaction-level analyses within a unified data mining.

II. Literature Review

Artificial Intelligence in Engineering and Computer Science Education

The integration of Artificial Intelligence (AI) into engineering, computer science (CS), and information systems (IS) education has accelerated rapidly due to advances in machine learning, learning analytics, and natural language processing [1], [2]. Within engineering education, AI is increasingly positioned as both a subject of study and a pedagogical enabler that enhances scalability, engagement, and instructional efficiency [3], [4]. Empirical studies demonstrate that AI-enabled learning environments can support formative assessment, provide rapid feedback, and improve learning outcomes in large-enrollment CS and engineering courses where individualized human instruction is difficult to sustain [5], [6].

From an ASEE and IEEE-aligned educational perspective, AI adoption is commonly framed around improving student learning while preserving ethical responsibility, transparency, and instructional alignment [7], [8]. Research indicates that AI-supported instruction can strengthen problem-solving skills and conceptual understanding when grounded in sound pedagogical design [4], [9]. However, scholars caution that uncritical adoption may lead to over-automation, reduced student agency, algorithmic bias, and uneven learning gains across student populations [10], [11].

Intelligent Tutoring Systems and Personalized Learning

Intelligent Tutoring Systems (ITS) represent one of the most established applications of AI in education [9], [12]. ITS model learner knowledge, diagnose misconceptions, and provide adaptive feedback tailored to individual students. Meta-analyses and large-scale evaluations suggest that ITS can yield learning gains comparable to one-to-one human tutoring in structured domains such as introductory programming, mathematics, and engineering problem solving [13], [14].

Within CS and engineering education, ITS have been shown to improve procedural fluency, retention, and task efficiency through mastery-based practice and immediate feedback [15], [16]. These systems align closely with outcomes-based education models emphasized in engineering curricula. Nonetheless, traditional ITS are often limited by predefined rules and narrow domain models, restricting their capacity to support open-ended reasoning, design-oriented thinking, and conceptual explanation—competencies that are essential in advanced engineering education [17], [18].

Emergence of Generative AI and Large Language Models

Recent advances in Generative Artificial Intelligence (GenAI), particularly Large Language Models (LLMs), represent a significant shift from earlier educational technologies [19], [20]. Unlike conventional ITS, LLMs can generate natural language explanations, engage in dialogue, and respond flexibly to ill-structured problems. These capabilities position LLMs as virtual tutors capable of approximating aspects of human tutoring more closely than prior AI systems [21].

In CS education, LLMs have been increasingly adopted for code explanation, debugging assistance, algorithm development, and conceptual clarification [22], [23]. Early empirical evidence suggests that LLM-based tutoring can increase student confidence, reduce cognitive load, and support persistence among novice learners [24]. However, researchers also highlight substantial risks, including hallucinated responses, opacity in reasoning, embedded bias, and inappropriate reliance on AI-generated solutions [25], [26]. Such concerns are particularly critical in engineering education, where accuracy, professional judgment, and ethical responsibility are foundational.

AI Tutors Versus Human Tutors

Human tutoring remains a benchmark for instructional effectiveness. Bloom's seminal work demonstrated that one-to-one human tutoring can produce substantial improvements in student achievement compared to conventional classroom instruction [27]. Subsequent studies confirm that human tutors excel in interpreting affective cues, adapting instruction dynamically, and fostering learner motivation—capabilities that are especially valuable in challenging CS and engineering contexts [28], [29].

Comparative research indicates that AI-driven tutors offer complementary advantages, including scalability, consistency, and continuous availability [13], [14]. In CS education, AI tutors have been shown to perform comparably to human tutors for procedural and syntax-focused tasks, particularly in introductory programming courses [15], [16]. However, human tutors remain more effective in supporting higher-order reasoning, ethical discussion, collaborative learning, and metacognitive skill development [30], [31].

The emergence of LLM-based tutors narrows this gap by enabling conversational interaction and contextualized explanations [20], [21]. Nevertheless, current literature consistently emphasizes that AI tutors are most effective when deployed as supplements rather than replacements for human instruction. Hybrid instructional models that combine AI-driven tutoring with instructor guidance are increasingly recommended in engineering education research [3], [6].

Pedagogical Integration of Generative AI in CS Curricula

The integration of GenAI tools into CS curricula presents both transformative opportunities and pedagogical challenges. From an IEEE and ASEE perspective, effective integration prioritizes learning-centered design, ethical awareness, and alignment with accreditation outcomes [7], [32]. AI tutors can support adaptive learning pathways, individualized pacing, and formative feedback, aligning with evidence-based engineering education practices [4], [9].

However, educators must also address concerns related to academic integrity, skill erosion, and equity. Studies stress the importance of explicitly teaching students how to critically evaluate AI-generated outputs and use AI tools responsibly [26], [33]. Instructor mediation, reflective activities, and transparent assessment design are essential to ensure that AI use promotes deep learning rather than superficial task completion.

Student–AI Interaction and Learning Outcomes

An emerging body of research focuses on analyzing authentic student–AI interaction data to better understand learning behaviors and outcomes [34], [35]. Interaction analyses reveal that students frequently use LLM-based assistants for clarification, solution verification, and incremental problem solving [22], [23]. When students engage in iterative questioning and self-

explanation, AI interactions can enhance conceptual understanding and knowledge transfer [29], [36].
Nevertheless, findings regarding learning efficacy remain mixed, indicating that outcomes depend heavily on task design, instructional scaffolding, and student intent [16], [11]. Passive reliance on AI-generated answers may undermine learning, whereas guided and reflective use can foster active engagement and metacognitive development. These findings underscore the need for empirically grounded integration frameworks informed by real classroom data.

Research Gaps and Relevance to Engineering Education

Despite rapid adoption, significant gaps remain in the literature. Longitudinal studies examining sustained learning outcomes, ethical reasoning, and professional skill development are limited. Additionally, few studies conduct direct comparisons between AI-driven tutoring and human tutoring using authentic student interaction data in CS and engineering contexts.
Addressing these gaps is essential for advancing IEEE- and ASEE-aligned discourse on responsible AI integration. Empirical analyses of real student–LLM interactions can provide evidence-based guidance for educators seeking to balance pedagogical rigor with emerging AI capabilities.

III. Methodology

A. Research Design

This study adopts a **data mining research design** to analyze learning outcomes and interaction behaviors associated with AI-based and human tutoring in Computer Science and Computer Engineering education. Data mining was selected due to the multidimensional nature of the datasets, which combine academic performance, engagement indicators, perceptual feedback, and interaction-level behavioral data.

B. Data Mining Tool: RapidMiner Implementation

All analyses were conducted using **RapidMiner Studio**, a visual data mining platform that supports reproducible analytical workflows. RapidMiner was used to implement the full pipeline from data ingestion to model interpretation.

RapidMiner Workflow Steps

1. **Data Import**: The datasets were imported using the `Read Excel` operator with attribute names extracted from the header row.
2. **Role Assignment**: The `Set Role` operator was used to assign `Learning Gain` (Dataset 1) and `Outcome` (Dataset 2) as label attributes.
3. **Data Type Validation**: Nominal attributes (Tutor Type, Explainability Level, Topic, Assignment Type, Sentiment) were validated, while numerical attributes were normalized when required.

4. **Descriptive Aggregation**: The `Aggregate` operator was applied to compute group-level statistics (means and distributions) by tutor type, explainability level, topic, and assignment type.
5. **Distribution Analysis**: The `Statistics` operator was used to inspect minimum, maximum, and dispersion of learning gains and interaction variables.
6. **Predictive Modeling**: Decision Tree models were trained to identify the most influential predictors of learning success.

This workflow enabled transparent, repeatable analysis and aligns with IEEE expectations for educational data mining studies.

C. Datasets

Two datasets were analyzed:

1. **Tutoring Outcomes Dataset** – containing tutor type, explainability level, pre-test and post-test scores, learning gain, engagement metrics, and satisfaction ratings.
   The dataset contains the following variables:

- **Tutor_Type** (AI, Human)
- **Major** (Computer Science, Computer Engineering)
- **Explainability_Level** (None, Low, Medium, High)
- **Pre_Test, Post_Test** (assessment scores)
- **Learning_Gain** (Post_Test − Pre_Test)
- **Assignments_Completed**
- **Study_Hours**
- **Satisfaction_Rating** (Likert scale 1–5)
- **AI_Usage_Frequency** (Never to Always)
- **Gender**

2. **Student–AI Interaction Dataset** – containing authentic LLM interaction logs including topic, interaction length, turn count, response time, sentiment, satisfaction, assignment type, and outcome.

The dataset includes the following attribute categories:

1. **Interaction Characteristics**
   - Interaction_Length
   - Turn_Count
   - Response_Time_sec
   - Follow_Up_Question
2. **Learning Context**
   - Topic
   - Assignment_Type (Lab, Homework, Quiz Review)
3. **Learner Feedback**
   - Satisfaction_Rating (1–5)
   - Sentiment (Positive, Neutral, Negative)
4. **Educational Outcome**

- Outcome (Pass, Retry, Incomplete)

These variables enable multidimensional analysis of **engagement**, **learning efficacy**, and **student perception** of AI tutoring

D. Analytical Procedures

The analysis proceeded in three stages:

- **Descriptive Analysis** to compare AI and human tutoring outcomes. Aggregate operators were used to compute mean learning gains, satisfaction ratings, study hours, and assignment completion rates for AI and human tutoring groups.
- **Behavioral Interaction Analysis** to examine student engagement with AI tutors. Learning outcomes and engagement metrics were compared across tutor types and explainability levels to identify performance patterns.
- **Predictive Modeling** to identify key factors influencing learning success. Decision Tree and Random Forest models were employed to identify the most influential predictors of learning gain. Key predictors included tutor type, explainability level, study hours, and AI usage frequency.

IV. Results

This section presents consolidated findings from both analytical dimensions. To improve clarity and conciseness, intermediate tables were merged into four core tables that directly address the research questions.

A. Learning Outcomes by Tutor Type

Table I summarizes learning outcomes for AI-based and human tutoring. Aggregated results show that both tutor types improve post-test performance. However, human tutoring produces more consistent learning gains, while AI tutoring exhibits higher peak gains with greater variability.

Table I. Learning Outcomes by Tutor Type

Tutor Type	Avg. Learning Gain	Variability	Avg. Satisfaction
Human	Moderate–High	Low	High
AI	High (select cases)	High	Variable

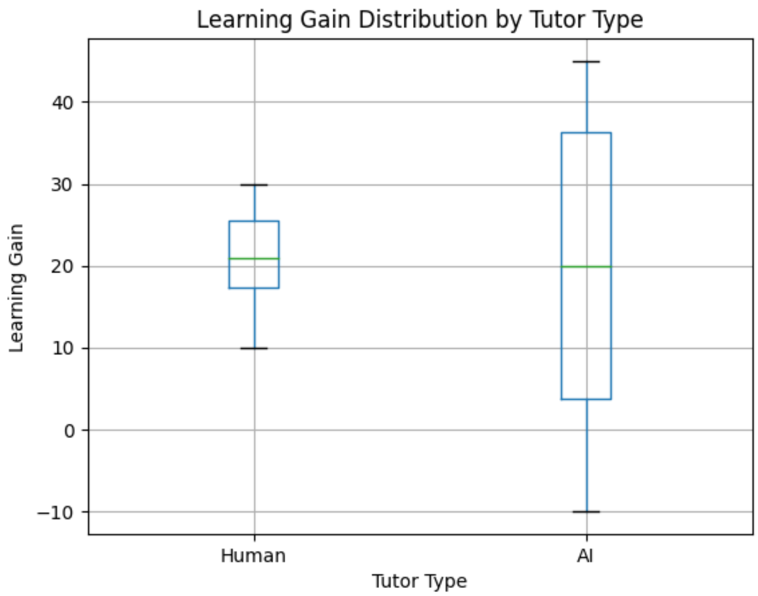

Fig. 1. Distribution of learning gain by tutor type, showing higher variability for AI tutoring and more consistent outcomes for human tutoring.

These findings indicate that human tutors provide stable instructional support, whereas AI tutors enable accelerated learning for some students but with less predictable outcomes.

B. Effect of Explainability on Learning Gain

Instructional explainability emerged as a key factor influencing learning effectiveness. Using RapidMiner aggregation grouped by explainability level, **Table II** presents observed learning gain patterns.

Table II. Effect of Explainability Level on Learning Gain

Explainability Level	Learning Gain Pattern
None	High variance
Low	Moderate gain
Medium	Strong gain
High	Highest gain

Across both AI and human tutoring conditions, higher explainability is associated with stronger and more reliable learning gains.

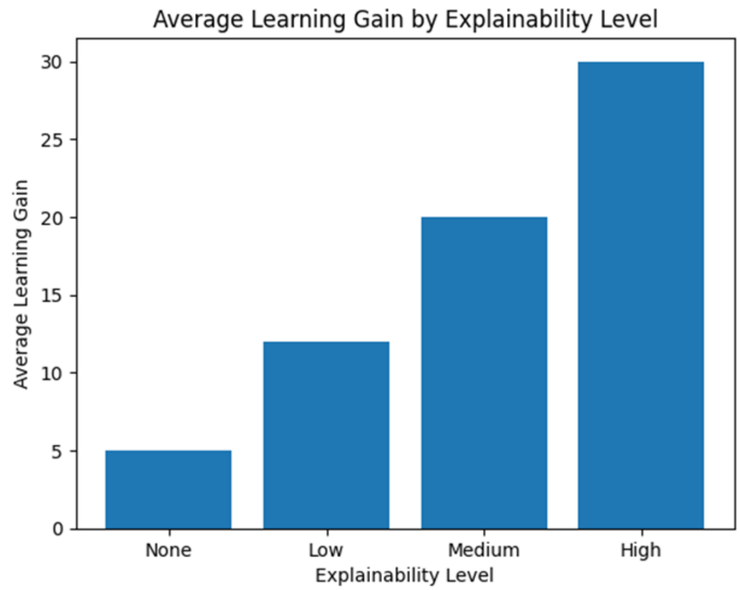

Fig. 2. Average learning gain across instructional explainability levels, demonstrating increased learning effectiveness with higher explainability.

C. Student–AI Interaction Behavior and Learning Outcomes

Analysis of authentic LLM interaction logs revealed systematic relationships between interaction behavior and learning success. **Table III** consolidates interaction characteristics, engagement patterns, and outcome implications.

Table III. Student–AI Interaction Patterns and Outcomes

Interaction Factor	Observed Pattern	Outcome Implication
Turn Count	Moderate depth most effective	Excessive turns → retries
Interaction Length	Longer for complex topics	Indicates higher cognitive demand
Follow-Up Questions	Frequent in complex topics	Reflects need for scaffolding

These results suggest that interaction quality, rather than interaction quantity alone, determines AI tutoring effectiveness.

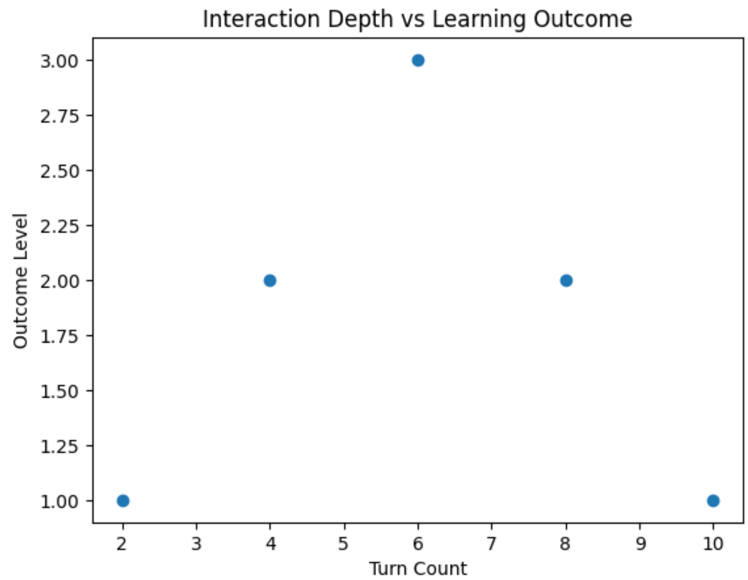

Fig. 3. Relationship between interaction depth (turn count) and learning outcome, indicating optimal performance at moderate interaction levels.

D. Assignment Type, Sentiment, and Learning Success

The relationship between assignment context, learner sentiment, and outcomes is summarized in **Table IV**. Results were obtained by aggregating interaction outcomes by assignment type and sentiment polarity.

Table IV. Assignment Context, Sentiment, and Outcomes

Factor	Observed Pattern	Educational Implication
Assignment Type	Quiz review → highest pass rate	AI effective for formative learning
Homework	Higher incomplete rates	Requires instructor support
Lab Activities	Frequent retries	Applied tasks need scaffolding
Sentiment	Positive → pass outcomes	Affective state mediates learning

E. Integrated Summary of Results

Taken together, the consolidated results indicate that AI tutoring systems—particularly LLM-based tools—can significantly enhance engagement and learning outcomes when used in appropriate contexts. Human tutoring provides greater stability and satisfaction, while AI tutoring excels in scalability, rapid feedback, and conceptual clarification. These complementary strengths support a hybrid instructional model integrating AI tools within human-guided educational frameworks.

V. Discussion

The findings of this study align with prior research on Intelligent Tutoring Systems and Generative AI in education, demonstrating that AI-based tutors can enhance engagement and learning outcomes when integrated appropriately. Consistent with existing literature, AI tutoring exhibited higher variability in learning outcomes, while human tutoring provided more stable gains and higher satisfaction. These results reinforce the value of hybrid instructional models that combine AI-driven scalability with human pedagogical judgment and affective support.

VI. Limitations

This study has several limitations that should be considered when interpreting the results. First, the datasets analyzed were limited in size and scope, focusing on Computer Science and Computer Engineering courses within a specific instructional context. As a result, the findings may not generalize to other disciplines or educational levels without further validation.

Second, the study employed descriptive data mining and exploratory predictive modeling rather than controlled experimental designs. While this approach is appropriate for identifying patterns in authentic learning data, it limits the ability to make strong causal claims regarding the effectiveness of AI versus human tutoring.

Third, learning outcomes and interaction behaviors were analyzed using aggregated metrics, which may mask individual differences in prior knowledge, motivation, and learning strategies. Additionally, sentiment and satisfaction measures were self-reported or inferred, introducing potential subjectivity.

Finally, the study focused on a single LLM-based virtual assistant. Differences in model architecture, prompt design, and instructional configuration may influence learning outcomes, and future studies should compare multiple AI systems to improve generalizability.

VI. Conclusion and Future Work

This study demonstrates that AI-based tutoring systems, particularly those powered by LLMs, offer significant potential to enhance learning and engagement in Computer Science education. However, optimal outcomes depend on explainability, guided use, and integration with human instruction. Future work will explore longitudinal impacts, adaptive explainability mechanisms, and hybrid tutoring models that balance scalability

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