Proceedings of International Conference on Islamic Education (ICIED)
Impactful Education: Integrating Technology, and Ecotheological Values For a Sustainable Future
Volume 10, 2025 (p-ISSN 2477-3638 / e-ISSN 2613-9804)

Effect of explainable artificial intelligence adaptive tutor on High School students' motivation and learning outcomes

Fifit L Marpaung[1], Ni Made Ameylia Sari[2], Reno[3], Heni Sulistiani[4]

Correspondence:
ni_made_ameylia_sari@teknokrat.ac.id

Affiliation:
Department of Informatics, Faculty of Engineering and Computer Science, Universitas Teknokrat Indonesia[1]
fifit_l_marpaung@teknokrat.ac.id

Department of Informatics, Faculty of Engineering and Computer Science, Universitas Teknokrat Indonesia[2]
ni_made_ameylia_sari@teknokrat.ac.id

Department of Informatics, Faculty of Engineering and Computer Science, Universitas Teknokrat Indonesia[3]
reno@teknokrat.ac.id

Master of Computer Science Study Program,Faculty of Engineering and Computer Science,Universitas Teknokrat Indonesia[4]
henisulistiani@teknokrat.ac.id

Abstract
The development of artificial intelligence (AI) in education has created new opportunities for the development of more customized learning environments. However, students' confidence and involvement tend to decline when traditional AI-powered educational systems lack transparency. This study examines how an adaptive tutoring system based on Explainable Artificial Intelligence (XAI) affects high school students' academic performance and motivation. Two learner groups were included in the quasi-experimental framework; one group used a conventional adaptive tutor, while the other group used a XAI-integrated adaptive tutor that was able to fully explain each instructional recommendation. Academic performance evaluations, motivation questionnaires, and system interaction logs were used to collect data. According to the results, students who used the XAI-enhanced instructor had much greater motivation and better learning outcomes than students in the control group. Students' self-control and confidence in their ability to learn were strengthened by the clear feedback systems, which enabled them to understand the reasoning behind instructional assistance. Overall, the study emphasizes how crucial explainability is to fostering learner trust, long-term engagement, and significant knowledge acquisition in AI-supported educational systems.

Keywords: Explainable Artificial Intelligence; Adaptive Tutor; Motivation; Learning Outcomes; High School Students

A. INTRODUCTION

Artificial intelligence (AI) has rapidly become a driving force in transforming modern educational practices. Its integration into classroom and digital learning environments enables instructional systems to tailor content based on students' performance, learning pace, and individual needs. Empirical studies (Chen et al., 2021; Kumar & Rose, 2019) consistently demonstrate that AI-powered adaptive learning can enhance engagement and academic outcomes by dynamically adjusting learning materials in response to students' progress. Such systems provide immediate feedback, targeted remediation, and appropriately leveled challenges—features that support learner autonomy, deeper cognitive processing, and long-term knowledge retention.

Despite these advantages, many existing AI-based tutoring systems rely on opaque or "black-box" algorithms. These systems often generate recommendations or feedback without explaining the underlying reasoning, which can result in learner confusion and decreased trust. When students cannot understand why certain suggestions are given, their motivation and confidence may decline, ultimately hindering the effectiveness of the learning experience (Holstein et al., 2019). Previous research shows that learners feel more secure, motivated, and engaged when instructional feedback is transparent and clearly connected to their learning goals (Gunning, 2017). Transparency, therefore, is not merely a technical requirement but a pedagogical necessity that shapes students' emotional and cognitive engagement.

Explainable Artificial Intelligence (XAI) has emerged as a promising approach to addressing this issue. By clarifying the logic behind AI-generated recommendations, XAI aims to improve the interpretability, trustworthiness, and reliability of educational interactions (Ribeiro et al., 2016; Lim et al., 2009). In learning contexts, XAI features can help students understand how adaptive decisions relate to their individual learning processes, thereby supporting self-regulation, persistence, and metacognitive awareness—especially during challenging tasks. Current findings in STEM and higher education contexts suggest that explainability can help learners feel more in control of their academic journeys.

However, despite increasing attention to XAI, most existing studies focus on university students or learners in technical domains. Limited empirical research has examined how explainability impacts secondary school students, particularly within adaptive tutoring environments. Prior studies often analyze either cognitive performance or technical aspects of XAI in isolation, overlooking its combined influence on motivation and academic achievement. Moreover, only a small number of studies have integrated explainable reasoning directly into adaptive systems designed specifically for adolescent learners—a notable gap given their developmental and instructional needs.

To address these limitations, the present study investigates how an XAI-enhanced adaptive tutoring system affects high school students' motivation and academic performance. By comparing an explainable adaptive tutor with a conventional adaptive tutor, this research seeks to determine whether transparent algorithmic feedback enhances both affective and cognitive learning outcomes. Specifically, the study aims to: examine how an XAI-based adaptive tutor influences students' learning motivation and evaluate the impact of the XAI-based adaptive tutor on students' academic achievement.

This study contributes to ongoing discussions on explainability in AI-supported education by offering empirical insights into how transparent feedback mechanisms can strengthen student trust, promote self-regulated learning, and enhance personalized learning experiences. Rather than proposing an entirely new concept, this work extends existing research to a population that has been understudied and provides practical implications for the development of future educational AI systems

B. METHODS

Design of Research This study investigated the impact of an Explainable Artificial Intelligence (XAI)-based adaptive tutor on students' learning motivation and outcomes using a quasi-experimental approach with a pretest–posttest control group structure. Group formation was conducted using a stratified assignment procedure. Students were first categorized based on their initial achievement levels (high, medium, or low), and then each ability stratum was randomly divided into a control group and an experimental group. This method was employed to ensure equivalence in baseline ability between the two groups. This design was utilized to allow comparisons between and within groups before and after the intervention period.

Participating

Sixty (60) eleventh-graders from SMAS K Kolese Santo Yusup (Kosayu) and SMAN3 Malang, Indonesia, voluntarily participated in the study. To ensure that all participants had similar educational backgrounds and prior understanding of the given topic, purposeful sampling was employed throughout the selection process. Thirty students made up the experimental group, while the remaining thirty made up the control group. The participants varied in age from 16 to 17, with equal representation of both genders. Before taking part, the schools and kids provided their informed consent.

Research Tools To gather data, three different kinds of equipment were used:

Motivation Questionnaire: Students' motivation levels were measured using a 20-item questionnaire adapted from the Motivated Strategies for Learning Questionnaire (MSLQ) developed by Pintrich et al. (1993). Each item used a 5-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). A pilot test was conducted to evaluate the reliability of the instrument, resulting in a Cronbach's alpha coefficient of 0.87, indicating good internal consistency.Since the original MSLQ was designed for college students and covers a broad set of motivational constructs, the items in this study were re-examined and adjusted to fit the context of high school learners and the specific objectives of the research. The adapted questionnaire focused on three key motivational aspects:

Intrinsic Motivation: Items measuring students' internal interest, enjoyment, and personal value in engaging with the learning material and the tutoring system.

Self-Efficacy: Statements assessing students' beliefs about their capability to understand tasks, complete assignments, and succeed academically when using the tutor.

Task Value: Items evaluating students' perceptions of the usefulness, importance, and relevance of the learning activities provided by the system.

These aspects were selected because they align with the study's goals and represent motivational constructs that are most relevant to secondary school students' engagement with adaptive tutoring systems.

Learning Achievement exam: The learning achievement exam consisted of **25 multiple-choice items** that assessed students' understanding of the **English subject**, specifically the topics covered in the tutoring materials. The test was reviewed by two experienced English teachers and pilot-tested to ensure appropriate item difficulty and discrimination levels.

Test Matrix (Blueprint)

The exam items were distributed according to the learning objectives and cognitive levels:

Vocabulary comprehension

(identifying meanings, synonyms, and contextual usage)

Reading comprehension

(understanding main ideas, details, and inferences)

Grammar understanding

(recognizing correct structures and forms)

Each topic was represented by several items to ensure content validity.

System Interaction Logs: The XAI adaptive teacher automatically recorded the amount of time spent on assignments, the number of exercises completed, and the frequency of system feedback access. These logs provided objective information on how students interacted with and utilized the system.

Location and Length of Research The two participating schools in Lampung, Indonesia, used computer laboratories to conduct the experiment. Over the course of the four-week intervention, students attended two sessions per week. Each learning session lasted around ninety (90) minutes. The experimental and control groups received the same educational resources through their different tutoring programs. Methodology The study underwent many consecutive procedures to ensure methodological consistency:

1. Giving both groups the motivation questionnaire and pretest before the intervention.
2. Presenting the two adaptive tutoring systems: the XAI tutor for the experimental group and the traditional tutor for the control group.
3. Holding two learning sessions per week for a duration of four weeks.
4. Gathering system interaction logs to track participation following each session.
5. After the session is over, give both groups the posttest and the final motivation questionnaire

This analytical process ensures the statistical validity and reproducibility of the study's findings. Furthermore, thorough methodological transparency makes it possible for other researchers to duplicate the study in comparable educational settings.

C. RESULT & DISCUSSION

Regarding the questionnaire results, the findings show that students who used the XAI-based adaptive tutoring system demonstrated higher motivation scores compared to those in the control group. These differences indicate that the explainable feedback features contributed to improved motivational responses across the measured aspects.

Table 1. Summary of Research Findings

No	Variable	Indicator	Finding Summary
1.	Leraning Outcomes	Mean Post-test Score Improvement	Students using XAI Tutor improved by 17 points, while control group increased by 11 points.
2	Learning Motivation	Engagement and Self-regulation	The experimental group demonstrated higher engagement and stronger self-regulation throughout the learning sessions.

Source: Research data (2025)

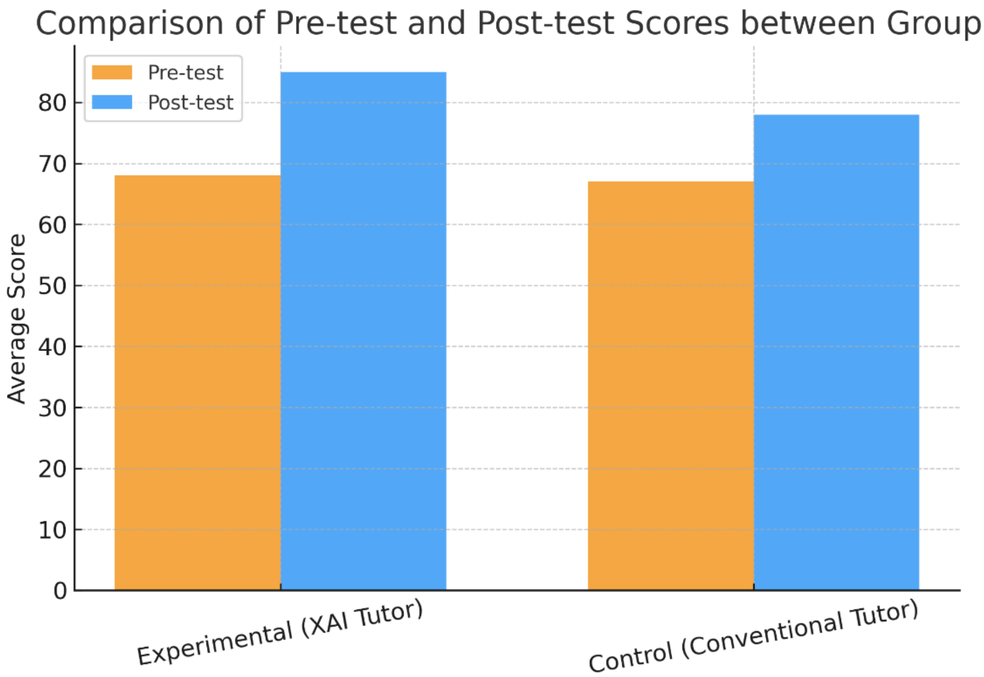

Figure 1. Comparing the Groups' Pre-test and Post-test Results

According to the quantitative analysis, the experimental group's mean post-test score was 85, whereas the control group's score was 68. The independent samples t-test results verified that this difference was statistically significant ($p < 0.05$). Additionally, the effect size (Cohen's d = 0.82) indicates that the XAI tutor has a substantial practical impact on students' learning outcomes. According to the motivation questionnaire results, students who interacted with the XAI-based system also demonstrated notable improvements in self-regulated learning, perseverance, and perceived autonomy. These findings suggest that the transparency provided by the XAI tutor not only enhances academic performance but also strengthens key motivational factors that support independent and sustained learning.

Discussion

The transparency and adaptive customisation of the XAI instructor are responsible for the notable increase in students' motivation and academic performance. Learners were able to comprehend why specific exercises or resources were recommended because of the tutor's explainable elements, which included graphic explanations of progress and reasons for feedback. They seem to feel more in control as a result of this understanding, which increases their involvement and effort investment.

The results of this study are in line with other research that emphasizes the benefits of openness in AI systems for education. Rahman and Kim (2024) revealed that transparent feedback promotes better perseverance during challenging learning tasks, whereas Zhou et al. (2023) indicated that learners exposed to explainable AI models exhibited enhanced trust and motivation. The current study supports these assertions by demonstrating that explainability leads to quantifiable learning improvements in addition to increasing students' faith in the system.

The findings are consistent with Deci and Ryan's (2000) Self-Determination Theory, which highlights the importance of relatedness, autonomy, and competence for long-term motivation. By giving students clear explanations for system feedback (autonomy), skill-appropriate adaptive tasks (competence), and interactive communication that promotes perceived support (relatedness), the XAI tutor meets these objectives. Deeper and more meaningful engagement with learning information is facilitated by this confluence of technology and psychological concepts.

The enhancement of self-regulated learning (SRL) activities is another important point this study emphasizes. Students who used the XAI tutor demonstrated a more proactive attitude to tracking their own development, efficiently managing their time, and asking questions when they ran into problems. This is consistent with Khosravi et al. (2022), who contend that students may more successfully adjust their learning tactics when they get explainable feedback. The larger number of completed exercises and longer time-on-task noted in system interaction logs in this study demonstrated SRL enhancement.

Furthermore, the idea that emotional and cognitive elements are interconnected in technology-enhanced learning environments is supported by the study's substantial correlation between motivation and performance. A learning ecology is created by transparent systems like XAI tutors, where feedback is both educational and confidence-boosting. Learners are more likely to absorb learning objectives and achieve better academic results when they comprehend the reasoning behind AI suggestions.

These findings have ramifications that go beyond immediate gains in learning. Teachers and developers may build intelligent systems that support lifelong learning skills, especially self-regulation and reflective awareness, by integrating explainability into adaptive algorithms. Additionally, ethical worries about algorithmic bias and student mistrust may be lessened by openness in AI systems, encouraging fair and reliable AI incorporation in learning environments.

Overall, the results of this quasi-experimental study show that maximizing the educational advantages of AI-based tutoring systems requires explainability. The XAI method produces a more comprehensive and human-centered learning experience by improving learners' cognitive and motivational engagement while also making machine reasoning more understandable.

D. CONCLUSION

The results of the study show that the Explainable Artificial Intelligence (XAI)-based adaptive tutor effectively improves students' academic performance and learning motivation. Students are better able to understand comments due to the system's openness, which increases trust and participation throughout the learning process. Compared to students who utilized the conventional teacher, those who used the XAI system demonstrated improved self-regulation and higher post-test results. Thus, explainability is a pedagogical component that encourages meaningful and independent learning in addition to being a technological characteristic. To further confirm these results, future studies should investigate XAI applications in more diverse scenarios.

REFERENCES

Chen, X., Huang, R., & Li, Y. (2021). *Adaptive learning systems and personalized education: A review of AI integration in classrooms*. **Computers & Education, 174**, Article 104130. https://doi.org/10.1016/j.compedu.2021.104130

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268.

Gunning, D. (2017). *Explainable artificial intelligence (XAI)*. Defense Advanced Research Projects Agency (DARPA). https://www.darpa.mil/program/explainable-artificial-intelligence

Holstein, K., McLaren, B. M., & Aleven, V. (2019). Designing for transparency and trust in human–AI systems for education. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(1), 776–783.

Khosravi, H., Buckingham Shum, S., Chen, G., Conati, C., Tsai, Y.-S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers & Education: Artificial Intelligence*, *3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Kumar, R., & Rose, C. P. (2019). Building conversational agents in educational settings: Towards explainable and adaptive tutors. *International Journal of Artificial Intelligence in Education*, *29*(1), 45–72.

Lim, B. Y., Dey, A. K., & Avrahami, D. (2009). Why and why not explanations improve the intelligibility of context-aware intelligent systems. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 2119–2128). ACM.

Marr, B. (2021). *Artificial intelligence in practice: How 50 successful companies used AI and machine learning to solve problems*. Wiley.

Pintrich, P. R., Smith, D. A. F., García, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801–813.

Rai, A. (2020). Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science*, *48*(1), 137–141.

Rahman, M., & Kim, J. (2024). Transparent AI feedback systems for enhancing student trust in adaptive learning. *Computers in Human Behavior*, *151*(2), Article 107222.

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). "Why should I trust you?" Explaining the predictions of any classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 1135–1144). ACM.

Russell, S. J., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Zhou, Y., Li, J., & Wang, T. (2023). Exploring explainability in AI-based education: Impacts on motivation and learning. Educational Technology Research and Development, 71(2), 254–276.

Marr, B. (2021). Artificial Intelligence in Practice: How 50 Successful Companies Used AI and Machine Learning to Solve Problems. Wiley.

Russell, S. J., & Norvig, P. (2020). Artificial Intelligence: A Modern Approach (4th ed.). Pearson.

UNESCO. (2022). *AI and education: Guidance for policy-makers*. https://unesdoc.unesco.org

Zhou, Y., Li, J., & Wang, T. (2023). Exploring explainability in AI-based education: Impacts on motivation and learning. *Educational Technology Research and Development*, *71*(2), 254–276.