Striking the Balance: Exploring Levels of AI Tutor Proactivity in Enhancing Online Self-Paced Learning

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ABSTRACT: This study examined the proactive role of Artificial Intelligence (AI) tutors in students' online lecture experiences. To achieve this, we designed and developed an AI tutor with four distinct proactivity levels: Reactive Support, Notification, Suggestion, and Active support. The AI tutor was embedded into the online lecture platform, where students could access and chat with the AI tutor during their lectures. Experiments were conducted with 8 students, where each participant engaged in a 15-minute online lecture with the AI tutor at different levels of proactivity. Using interaction log data, quiz scores, and survey and interview responses, students' learning ownership, engagement, and outcome were measured and compared across groups with four proactivity levels for the AI tutor. Findings showed that the AI tutor's higher proactivity positively influenced students' learning outcomes, while leading to a decrease in students' sense of ownership and engagement. The findings highlight the importance of a balanced approach to AI tutor proactivity, where tailored, adaptive interventions can enhance learning outcomes without compromising learner autonomy and engagement in self-paced online environments.

Keywords: generative AI, conversational agents, AI tutor, proactiveness, online self-paced learning, personalized learning, learning ownership, learning engagement

1 Introduction

With the expansion of remote education systems, Artificial Intelligence (AI) tutors play an increasingly essential role in supporting effective, self-paced online learning. In typical educational settings, teachers often play a critical role in monitoring student progress and offering timely support to guide student focus. AI chatbots are expected to take a teacher role in online self-paced learning through on-the-spot interactions (e.g., asking questions to AI and receiving instant responses generated), helping students stay engaged and address challenges simultaneously (Baillifard et al., 2024). Particularly, the *proactive* aspect of AI tutors received attention with the potential of fulfilling learner needs and providing timely information, often without explicit user requests (Meurisch et al., 2020; Deng et al., 2024). However, in most practices of leveraging AI chatbots into online learning, AI tutors often operate in a *passive* and *reactive* manner, failing to fully replicate the dynamic, responsive teacher-student interactions found in traditional face-to-face classroom settings (Baillifard et al., 2024).

This study explores the potential of how AI tutors can function *proactively* in providing timely support for online self-paced learning, with a particular focus on determining the appropriate level of proactive intervention for effective support. A generative AI-based tutor was designed with four levels of proactivity based on the literature review (Reactive Support, Notification, Suggestion, and Active Support), and then tested with 8 students to examine how the AI tutor proactively intervenes in real online learning scenarios. Using interaction log data, quiz scores, and survey and interview responses, students' learning ownership, engagement, and outcome were measured and compared across groups, each of which had selected one of the four proactivity levels for the AI tutor. The findings contribute to the knowledge base for optimizing AI tutor proactivity to foster meaningful online self-paced learning experiences, laying the groundwork for further exploration and dialogue.

2 Design and Context for Proactive AI Tutor System

The proactive AI tutor was built using the GPT-3.5-turbo model and integrated into a web-based platform using HTML, CSS, JavaScript, and Flask API. Students were exposed to a 15-minute lecture on reinforcement learning, followed by a quiz, post-survey, and interview. The AI tutor took three key tasks at different points of learning: (1) generating educational materials before learning (e.g., learning objectives, quiz questions, and intervention messages); (2) responding to students' real-time prompt messages; (3) delivering the prepared materials from step 1 at predetermined times. Before a student started watching the lecture video, the AI tutor was used to create the educational materials and embed them into the learning platform (see Figure 1). The AI tutor extracted learning objectives from the lecture text (e.g., "*Explain the roles of agents and rewards in reinforcement learning*") and created O/X quiz questions, setting them up before learning began. Then, the AI tutor generated a set of appropriate intervention messages at specific points (e.g., *"At this point, understanding the roles of agents and rewards is crucial. If needed, I can create a simple quiz to check your understanding."*) During the 15-minute online lecture, the AI tutor intervened in the student's learning process by providing tailored prompts, according to each student's selected level of proactivity among four options, which were selected based on the literature (Deng et al., 2024; Oh et al., 2024; see Figure 1). At the **Reactive Support** level, the tutor only responded to student-initiated queries. The **Notification** level automatically informed students of key points during the lecture, while the **Suggestion** level offered optional supplementary materials on key topics. At the **Active Support** level, the tutor paused the lecture to present critical content, requiring student review before proceeding.

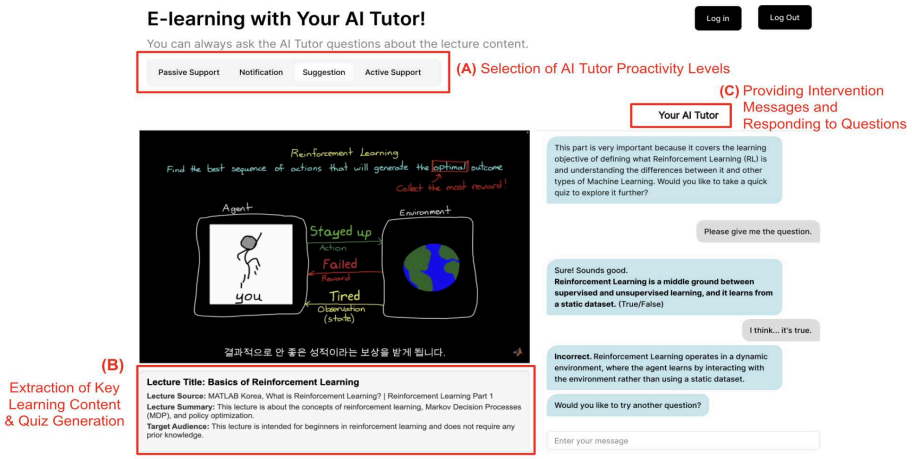

Figure 1: The proactive AI tutor embedded in a web-based self-paced learning platform

2 In-Situ Examination of the Role of AI Tutor Proactivity on Learning

The study involved eight graduate students (ages 24–34) enrolled in a Deep Learning course at a large private university in South Korea, all of whom lacked prior experience in reinforcement learning. Each participant engaged in a 30-minute intervention within an online self-paced learning environment using a between-subject design. After the session, we collected multiple data types: (1) interaction log data with the AI tutor (including the number of questions asked to measure *behavioral engagement*), (2) quiz scores on a 20-item test to measure *learning outcomes*, and (3) survey responses assessing *ownership* (the level of control and satisfaction a student feel over their learning while using AI tutor) and *cognitive engagement* (the extent to which a student maintains their focus on learning through constant interaction), with two items for each on a 7-point Likert scale, alongside interview responses to explore the rationale behind their survey ratings. We then analyzed differences in reported ownership, engagement, and learning outcomes (quiz scores) across groups of two students, each of which had selected one of the four proactivity levels for the AI tutor.

The results revealed varying impacts of AI tutor proactivity levels on student ownership, engagement, and learning outcomes. For *learning ownership*, the Reactive Support level received the highest score (M = 7), followed by Notification (M = 6), Suggestion (M = 3), and Active Support (M = 4.5). These results show that higher proactivity diminished students' perceived control over their learning. *Behavioral engagement*, measured by the number of student-initiated questions, was highest with Reactive Support (M = 5) and Notification (M = 4), while engagement dropped significantly with the Suggestion (M = 1.5) and Active Support levels (M = 1), indicating a decline in voluntary participation as proactivity increased. However, in *cognitive engagement*, measured by the extent to which they maintain their focus through continuing interaction, the different proactivity levels had minimal effect, indicating that proactive interventions did not disrupt the learning process. Finally, *learning outcomes*, measured by a 20-question quiz, were highest at the Active Support level (M = 18.75), followed by the Suggestion (M = 18.5), Notification (M = 16.5), and Reactive Support levels (M = 15.5), suggesting that increased proactivity showed higher learning outcomes.

3 Discussion

Our research explored the role of AI tutor proactiveness in shaping students' online self-paced learning experiences. Specifically, we designed the AI tutor to operate at different levels of proactivity and implemented it in real learning environments, conducting an in-situ examination of its meaningful affordance in practice. The findings reveal a dual role of AI tutor proactivity in online self-paced learning. While higher levels of proactivity might enhance learning outcomes and stimulate additional activities, they may inadvertently reduce learners' sense of ownership. This suggests that AI tutors should be carefully calibrated to balance proactive support with the need for learners to maintain control and autonomy over their learning experience. However, the findings also showed that groups with higher proactivity levels showed reduced perceptions of control over the learning process and lower behavioral engagement. The observed decrease in behavioral engagement among students with more proactive AI tutors might suggest that too much intervention may inhibit voluntary student participation. This decrease underscores the importance of designing AI tutor systems that encourage, rather than replace, active engagement. For effective online self-paced learning, AI tutor interventions might be adjusted to prompt student-initiated actions without overwhelming their learning process. These findings suggest several pathways for refining AI tutor design in self-paced learning contexts; integrating real-time monitoring and adaptive proactivity levels could enable AI tutors to dynamically adjust to learners' evolving needs, ensuring that support is neither overly intrusive nor overly passive (Meurisch et al., 2020; Deng et al., 2024). Further research might explore the development of AI tutor systems that promote both high engagement and autonomous learning by leveraging insights from these results. Together, this study highlights the importance of a balanced approach to AI tutor proactivity, where tailored, adaptive interventions can enhance learning outcomes without compromising learner autonomy and engagement in self-paced online environments.

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