

Human Interaction Model Part 2:  
Asynchronous Learning Process Model

Liam O'Neill

Abdur Rafay Saleem

Robert C. Wilson

University of Central Florida

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Dr. Roger Azevedo

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### **Abstract**

This paper presents a human interaction model of an asynchronous learning environment where a student engages with an AI-powered educational platform under the guidance of a professor. The AI system employs reinforcement learning to dynamically adjust the difficulty of instructional materials, ensuring adaptive scaffolding that aligns with the student's evolving knowledge and skill level. As the student interacts with the platform to assess prior knowledge and acquire new concepts, the AI continuously refines its instructional approach based on performance data. The professor receives real-time analytics on student progress, allowing for targeted curriculum adjustments to optimize learning outcomes. By integrating cognitive-emotional regulation principles, this model fosters a responsive and personalized educational experience, enhancing student engagement and knowledge retention in virtual learning environments.

**Topic**

The integration of artificial intelligence into educational environments is reshaping the way students engage with course material, offering new avenues for adaptive learning and personalized instruction. Reinforcement learning-based AI platforms provide dynamic difficulty adjustments, ensuring the instructional content evolves with the student's cognitive progress. The model supports asynchronous learning and enhances adaptive scaffolding which allows the student to receive tailored support that aligns with their learning pace and comprehension levels.

Advances in educational technology have created new opportunities and influenced traditional methods with AI-driven learning platforms as the latest development. By utilizing cognitive-emotional regulation principles, these platforms can monitor student engagement and adjust feedback strategies to prevent cognitive overload while fostering motivation. Research suggests that adaptive scaffolding techniques improve learning efficiency by offering targeted interventions when students struggle (Roll, Alevan, McLaren, & Koedinger, 2011). Additionally, reinforcement learning algorithms have been shown to optimize learning trajectories by tailoring content difficulty based on student performance (Chen, Saeedvand, & Lai, 2023). The ability of AI to analyze student interactions and provide real-time insights allows educators to refine curriculum design, making learning environments more responsive and effective (Fadel, Holmes, & Bialik, 2019).

From a modeling and simulation perspective, capturing the interactions between students, AI platforms, and instructors is crucial for developing robust educational frameworks. AI-enhanced learning models can simulate cognitive processes and predict student outcomes, aiding instructors in crafting data-driven instructional strategies. The inclusion of machine learning in education research enables the continuous refinement of these models, improving engagement

and retention rates in virtual learning spaces. As these intelligent systems become more sophisticated, they offer promising pathways for scalable, inclusive, and personalized education.

### **Scenario**

The scenario has been updated to be more subject agnostic. The instructor designs concise, structured learning modules adaptable across various subjects and tailored for diverse student backgrounds. Each module employs a consistent three-step approach: (1) presentation of core concepts by the instructor, (2) demonstration of practical applications, and (3) student engagement through interactive exercises and assessments. Using adaptive scaffolding techniques, the instructor incrementally supports student mastery by dynamically adjusting content complexity based on continuous monitoring of student performance and engagement. Although primarily designed for asynchronous delivery, the structure is versatile enough to accommodate synchronous teaching environments.

A key change to the scenario is the human-to-human component represented through the students and their interactive learning environment. Students initially engage by activating prior knowledge, providing a foundation for integrating new information. They then actively employ cognitive processes such as evaluation, reasoning, and adaptive strategies when interacting with learning materials. Continuous practice and timely feedback promote solidification of both procedural and declarative memory. Additionally, students' emotional and cognitive states are taken into consideration to enable personalized learning that respond to their individual student needs and learning challenges.

## Describe the human, task/activity, and context

*The Human.* The instructor in this scenario is an expert educator with advanced subject knowledge and strong pedagogical skills. Their role is to create comprehensive and engaging educational content accessible to students of varying academic backgrounds and learning styles. The instructor utilizes



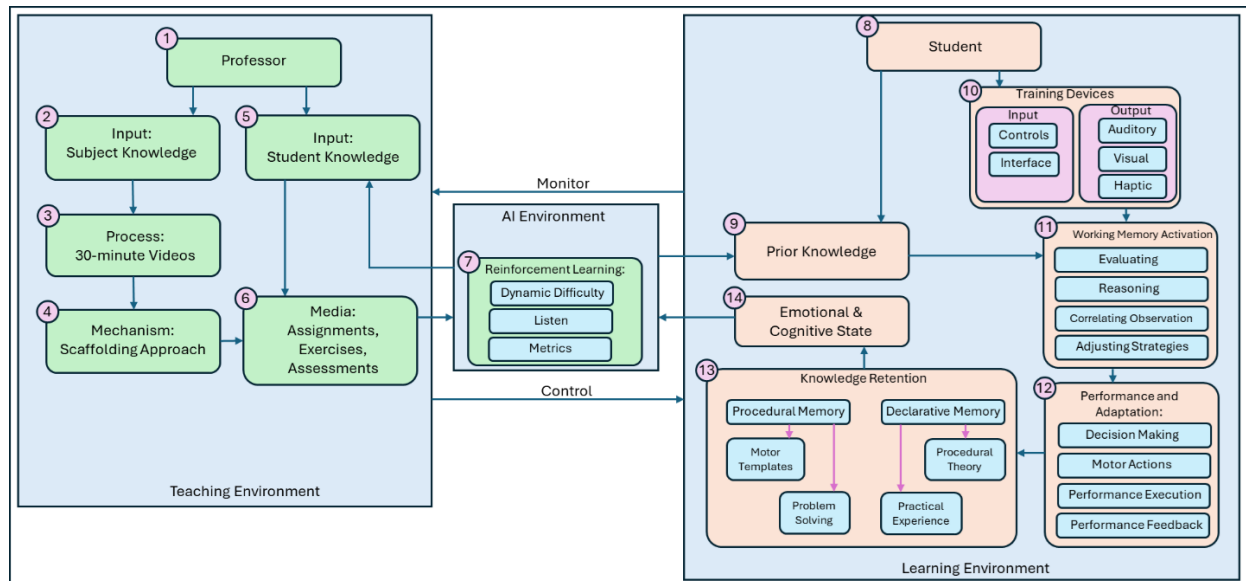
Figure 1. Image generated using the prompt "Asynchronous learning for professor and student" by Stability AI, Stable Diffusion 3, March 12, 2025

their understanding of instructional strategies to facilitate incremental and adaptive learning (Spadafora & Downes, 2020).

*The Task/Activity.* The instructor designs and delivers asynchronous educational modules using a structured three-step instructional process. These modules incorporate video lectures or demonstrations, interactive activities, and assessments to actively involve students. The instructor employs adaptive scaffolding strategies, iterating on prior knowledge and adjusting instructional complexity based on monitoring of student performance and engagement metrics (Bonabeau, 2002).

*The Context.* The learning environment is entirely online and asynchronous, allowing geographically dispersed students to access educational content flexibly according to their schedules. Students interact with course materials through digital platforms such as learning management systems (LMS) and communication tools like discussion boards or chat applications. The asynchronous setting requires planning and sequencing of instructional content, anticipation of potential student misunderstandings, and continuous analysis of learner performance to maintain engagement and ensure progression through the course.

## Human Interaction Model (Rafay)



The human interaction model presents a framework for understanding the complex dynamics of educational environments, structured around two primary domains: the Teaching Environment and the Learning Environment, interconnected through advanced monitoring and adaptive learning mechanisms.

The Teaching Environment originates with the Professor (1), who serves as the central orchestrator of the learning experience. Unlike traditional teaching approaches, this model emphasizes a dynamic, responsive approach to curriculum design. The professor integrates two critical inputs: Subject Knowledge (2) and Student Knowledge (5). Subject Knowledge encompasses the comprehensive understanding of the discipline, while Student Knowledge represents a nuanced understanding of learners' backgrounds, existing skills, and individual learning needs.

The process of content delivery transcends traditional lecture methods, utilizing specialized 30-minute modules (3) designed to maintain cognitive engagement and minimize information overload. These modules are carefully crafted to introduce complex concepts in

digestible segments, providing a foundation for subsequent practical exercises. A sophisticated Scaffolding Mechanism (4) underpins this approach, strategically breaking down complex tasks into manageable steps and progressively reducing supportive structures as the learner demonstrates increasing competence.

Central to the model's innovation is the Reinforcement Learning system (7), which serves as a bidirectional bridge between the professor and the students. This adaptive mechanism dynamically analyzes performance data generated through Media (6), including assignments, exercises, and assessments. (Anderson, 2009)

The Reinforcement Learning system represents a sophisticated approach to educational interaction, integrating three critical components that work in concert to create a responsive learning environment. The Dynamic Difficulty component lies at the heart of this system, enabling a nuanced approach to challenge management. This mechanism carefully calibrates the complexity of learning tasks, ensuring that students are consistently positioned at the edge of their current capabilities. By making minute adjustments to task difficulty, the system prevents both the frustration of overwhelming challenges and the disengagement that comes from tasks that are too simple.

The Listen mechanism represents the system's sophisticated data collection and interpretation capabilities. Far more than a passive recording tool, this component actively captures the subtle nuances of student interactions. It tracks not just explicit performance metrics, but also the underlying patterns of engagement, learning behaviors, and potential cognitive struggles. This deep listening approach allows the system to develop a rich, multidimensional understanding of each student's learning journey, identifying both obvious and hidden learning opportunities.

The Metrics generation component transforms raw data into meaningful educational insights. This is where the system's analytical power truly becomes apparent. By converting complex performance data into comprehensible and actionable intelligence, the metrics component provides a clear lens through which both students and professors can understand learning progress. It goes beyond simple numerical scoring, creating comprehensive performance profiles that capture the complexity of the learning process. By continuously monitoring learner interactions, the system can adjust task difficulty, learning style, and content complexity in real-time, maintaining an optimal challenge level that sustains motivation and promotes skill development. The interconnected nature of these components ensures a dynamic, responsive educational experience that adapts seamlessly to individual learning needs.

The Learning Environment focuses intensely on the Student (8), focusing on the cognitive and emotional journey. The student engages with learning materials through a self-paced, adaptive approach guided by the professor's structured framework and the system's intelligent feedback mechanisms. This environment recognizes learning as a complex interplay of cognitive processes, emotional states, and prior experiences.

Prior Knowledge (9) serves as a foundational element, representing the learner's existing mental models and familiarity with the subject matter. This component can either accelerate learning when aligned with new material or potentially create obstacles if misconceptions exist. Working Memory Activation (11) becomes crucial in this context, enabling the student to manage complex information, juggle multiple conceptual relationships, and execute precise cognitive tasks.

The model acknowledges the profound impact of the student's Emotional and Cognitive State (14) on learning outcomes. Emotions such as excitement, frustration, and cognitive states



like alertness or fatigue significantly influence attention, persistence, and problem-solving capabilities. Sophisticated indicators like time-on-task and help-seeking behaviors provide insights into the learner's psychological learning landscape.

Knowledge Retention (13) emerges as a critical mechanism for transforming temporary understanding into durable skill mastery. Through repeated practice, meaningful feedback, and carefully sequenced tasks, the model ensures that knowledge transitions effectively from short-term to long-term memory.

A dynamic Decision Point mechanism (12) allows students to choose cognitive strategies actively. At various stages, learners can decide how to approach challenges, whether by reviewing tutorial materials, seeking expert support, or experimenting independently. These decision points reflect a complex interplay between prior knowledge, working memory capacity, emotional state, and the adaptive feedback systems.

By integrating advanced cognitive science, adaptive learning technologies, and a holistic understanding of human learning processes, this model represents a groundbreaking approach to understanding educational interactions that transcends traditional pedagogical methodologies.

The diagram illustrates the intricate connections between these components, with monitoring and control mechanisms ensuring a continuous, adaptive learning experience that responds dynamically to individual learner needs and capabilities.

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