2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #50683

Bridging Cognitive and Motor Learning through XR-Enabled Intelligent Tutoring Systems

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Dr. Ali Barenji's research focuses on the design and development of intelligent, resilient, and adaptive systems for next-generation manufacturing, logistics, and healthcare. His work integrates robotics, cognitive artificial intelligence, extended reality (XR), digital twins, and human-machine interaction to create human-centric, flexible, and secure industrial solutions.

Bridging Cognitive and Motor Learning in Human-Robot Collaboration through XR-Enabled Intelligent Tutoring Systems

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Abstract
As Industry 5.0 emphasizes human-centric manufacturing, the ability to work effectively within Human-Robot Collaborative (HRC) systems is becoming a critical workforce competency. However, training for HRC is fraught with safety risks and resource constraints; novice errors in close-proximity human-robot interaction can lead to injury or equipment damage. This study presents the design and evaluation of an XR-enhanced Intelligent Tutoring Environment (XR-ITE) specifically tailored for collaborative sorting tasks. The environment integrates Extended Reality (XR) with a digital twin of a collaborative robot (cobot) to foster the psychomotor skills required for shared-workspace operations. Unlike static training simulations, the XR-ITE employs an intelligent agent that monitors human-robot spatial synchronization, handover efficiency, and safety zone violations. Learners engage in a collaborative sorting scenario where they must coordinate actions with the virtual cobot while receiving real-time, multimodal feedback on their trajectory and timing. Empirical results demonstrate significant improvements in situational awareness, task efficiency, and safety compliance compared to traditional video-based instruction. The findings suggest that XR-ITEs can effectively bridge the gap between theoretical safety knowledge and the dynamic motor skills required for safe human-robot teaming.
Keywords:

1. Introduction

The manufacturing and logistics landscape are currently undergoing a paradigm shift from Industry 4.0(I4.0), characterized by isolated automation, toward Industry 5.0(I5.0), which prioritizes human-centricity and resilient workforce ecosystems [1]. At the heart of this transition is Human-Robot Collaboration (HRC), where human workers and collaborative robots (cobots) operate in shared workspaces without physical barriers. Unlike traditional industrial robotics, where machines perform repetitive tasks in isolation, HRC requires a high degree of fluency, a seamless choreography where humans and robots synchronize their movements to perform a task. While this collaboration combines the cognitive flexibility of humans with the precision of robotics, it introduces a critical pedagogical challenge that is closely related to an unprepared workforce that is not ready to work alongside autonomous agents due to new and unfamiliar psychomotor demands[2].

The skill set required for I5.0 differs fundamentally from traditional operation. It extends beyond the manipulation of tools to include spatiotemporal reasoning and dynamic risk assessment. A worker must not only perform their tasks but also simultaneously anticipate the robot's trajectory, maintain awareness of the robot's varying velocity, and intuitively respect safety zones defined by standards such as ISO/TS 15066 [3]. In traditional training environments, developing this "collaborative intuition" is tense with challenges. Physical training with real robots carries inherent safety risks for novices, who may suffer from "tunnel vision" and fail to react to robot movements, leading to collisions or emergency stops that disrupt production. Besides creating effective physical training environment to train not only expansive for some cases not possible [4], [5]. Conversely, classroom-based instruction or video tutorials while safe and budget friendly fail to convey the spatial reality of the interaction, leaving learners with a theoretical understanding of safety but no embodied motor memory of how to move effectively around the machine.

Extended Reality (XR) and Artificial Intelligence (AI) have emerged as promising modality to bridge this gap, offering immersive, risk-free environments for practice [6]. However, current XR training solutions often function as passive simulators. They may visualize a robot, but they lack the pedagogical scaffolding required to correct unsafe behaviors or optimize collaborative efficiency. A novice in a standard VR simulation might complete a task successfully but inefficiently or innocently disrupt safety protocols that would cause an injury in the real world. To address these limitations, this study presents the design and evaluation of an XR-Enhanced Intelligent Tutoring Environment (XR-ITE) specifically the integration of AI. By integrating a high-fidelity digital twin of a cobot with an intelligent pedagogical agent, the XR-ITE provides real-time, multimodal feedback on the learner's performance. The system does not just track task completion; it actively monitors the user's kinematic data relative to the robot's motion, providing haptic and visual cues to guide the user toward safe, high-fluency interaction patterns. This paper details the system architecture, the integration of safety standards into the virtual environment, and an empirical evaluation comparing the efficacy of XR-ITE against traditional instruction in fostering safe and efficient human-robot teaming.

2. System Architecture: The XR-ITE Framework for collaborative robots

The XR-ITE Framework for collaborative robots is designed to create a closed-loop learning system where the learner's physical movements directly influence the tutoring logic. The system is built upon a modular framework consisting of three primary layers: the Physical-Virtual Integration (PVI) Layer, the Cognitive Modeling Layer (CML), and the Adaptive Feedback Layer (AFL). Figure 1 shows the proposed framework.

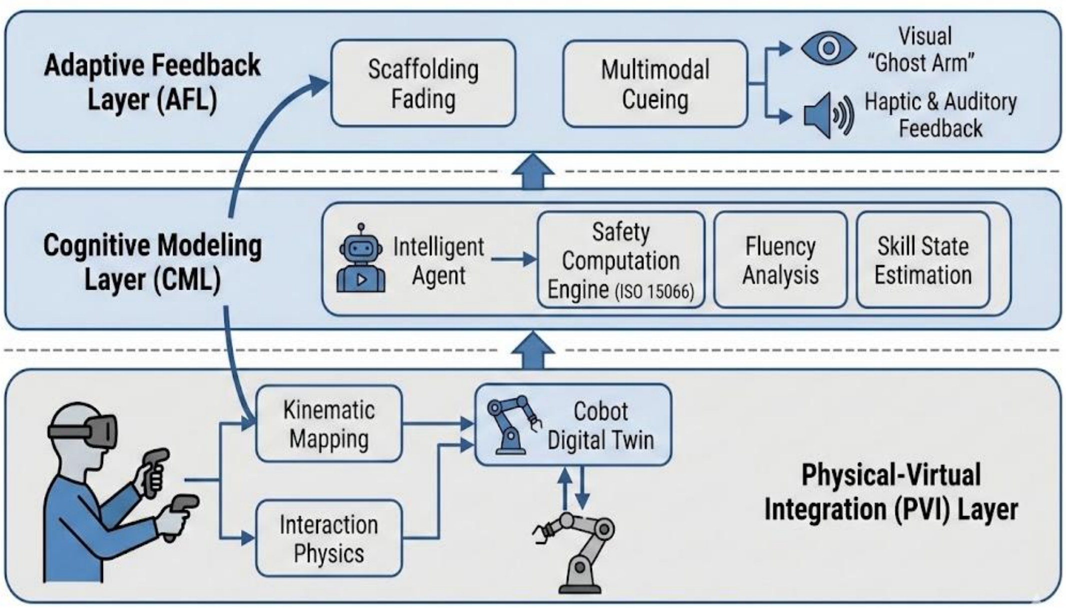

Figure 1 XR-ITS for Robot collaborative environment

2.1. Physical-Virtual Integration Layer

The PVI layer serves as the sensory bridge between the learner’s physical reality and the simulated workspace. Its primary function is to maintain high-fidelity synchronization between the human operator and the Cobot Digital Twin.

- Kinematic Mapping: This module captures 6-DOF (Degrees of Freedom) positional and rotational data from the learner's XR controllers and head-mounted display. It maps these physical inputs to a virtual avatar in real-time (< 11 ms latency) to ensure a seamless sense of embodiment.
- Environmental Synchronization: The PVI layer manages the state of the collaborative robot. It ensures that the virtual robot's joint velocities and singularities match the physics of a real industrial arm, providing the learner with realistic expectations of robot behavior.
- Interaction Physics: This component handles collision detection logic. It discerns between "intentional interactions" (e.g., grabbing a part) and "safety violations" (e.g., colliding with the moving robot arm), passing this raw event data up to the Cognitive Modeling Layer.

2.2 Cognitive Modeling Layer

The CML serves as the analytical core of the XR-ITE, transforming raw kinematic data from the PVI layer into pedagogical insights. It utilizes a comparator mechanism that evaluates the learner's real-time trajectory against a pre-recorded Expert Benchmark (a "gold standard" kinematic profile of the task). Figure 2 shows the capturing and visualization of expert kinematic trajectory concepts.

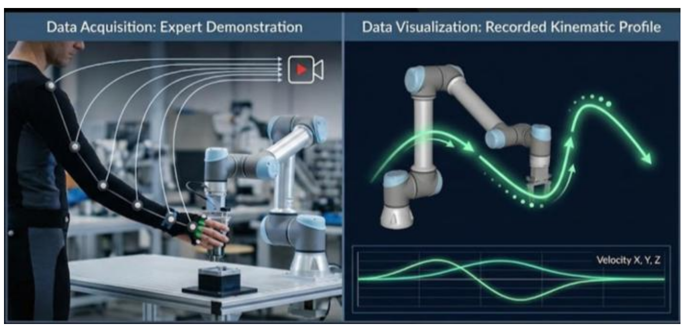

Figure 2 Capturing expert kinematic trajectory

- Safety Computation Engine: unlike standard physics engines that detect collisions only upon impact, this module implements predictive safety logic based on ISO/TS 15066. It continuously computes the Protective Separation Distance (S_p), a dynamic threshold that expands or contracts based on the relative velocity of the robot and the human hand. This allows the system to detect and penalize "Near-Miss" events instances where the learner violates the safety margin without causing a physical collision thereby correcting reckless behavior before it becomes a habit.
- Fluency Analysis: To assess collaborative efficiency, the CML quantifies the synchronization between the agent and the human. It tracks Robot Idle Time (RIT), which indicates a failure by the human to keep pace, and Human Idle Time (HIT), which suggests a lack of trajectory anticipation. High latency in either metric trigger specific interventions to improve the learner's spatiotemporal reasoning.
- Skill State Estimation: The system employs a Bayesian Knowledge Tracing (BKT) algorithm to maintain a dynamic probabilistic model of the learner’s proficiency [7]. As the learner successfully completes task segments without safety violations, the probability metric increases. This value directly controls the Adaptive Feedback Layer, determining when to "fade" (remove) visual scaffolding to transition the learner from supported practice to autonomous mastery.

2.3. Adaptive Feedback Layer

The AFL is the output interface responsible for closing the learning loop. Based on the assessment from the CML, it dynamically selects and renders the appropriate pedagogical scaffolding without overwhelming the learner's cognitive load.

- Multimodal Cueing: The layer orchestrates feedback across sensory channels.
    - *Visual:* Renders the "Ghost Arm" visualization (showing the robot's future path) to aid in trajectory prediction.
    - *Haptic:* Triggers vibration motors with varying intensity to simulate "force fields" when the user breaches safety zones.
- Scaffolding Fading: The AFL implements a "fading" strategy. As the CML reports an increase in learner proficiency, the AFL automatically reduces the frequency and intensity of cues (e.g., removing the visual path indicators), forcing the learner to rely on their own internal motor schema rather than external aids.

3. Implementation and Case Study

To validate the proposed XR-ITE architecture, we developed a functional prototype tailored for a high-frequency Human-Robot Collaborative (HRC) Sorting and Sourcing scenario. This section details the hardware/software integration and the specific industrial workflow used for evaluation. The system utilizes a distributed architecture that decouples the visualization layer from the control logic, ensuring that the "Digital Twin" behaves identically to the physical system. The implementation integrates Unity 3D (2022 LTS) for the XR interface with ROS 2 Humble for robotic control. The physical testbed (and its corresponding Digital Twin) utilizes the OS-101, a 6-DOF open-source robotic manipulator. This platform was selected to demonstrate the scalability of XR training for accessible, low-cost automation solutions in small-to-medium enterprises (SMEs). The arm is controlled via a custom ROS 2 hardware interface that communicates with the motor drivers over a serial bus. Figure 3 shows the implement case study in the lab environment.

Figure 3 Implementation and Case Study

4. Case Study: Collaborative Gearbox Assembly

To test the system's ability to train psychomotor skills, we designed a collaborative sorting scenario. This scenario mimics a "Quality Control and Kitting" station where a robot retrieves raw materials (sourcing), and a human operator inspects and sorts them. This task requires high-frequency interaction in a shared workspace. The workflow consists of three distinct phases, each targeting specific psychomotor competencies:

Phase 1: Dynamic Retrieval

The robot autonomously identifies and picks apart from the "Unsorted Bin" using a gripper. It then moves the part toward the "Handover Zone."

- The Challenge: The robot arm moves rapidly across the user's field of view.
- Psychomotor Skill: Trajectory Prediction. The user must learn to identify the robot's approach vector and keep their arms clear of the transit path.
- XR-ITE Support: The system renders a "Ghost Arm" (a translucent visualization) showing the robot's planned path 2 seconds into the future, allowing the user to step back or adjust their posture preemptively.

Phase 2: Collaborative Handover

The robot pauses at the "Handover Zone" and waits for the human to retrieve the object.

- The Challenge: The user must grasp the object from the robot's gripper without colliding with the robot's structure.
- Psychomotor Skill: Fine Motor Precision & Timing. The user must synchronize their grasp with the robot's release signal.
- XR-ITE Support: Visual cues (Green/Red bounding boxes) indicate when the robot has reached a stable handover state. If the user approaches too aggressively (high velocity), the system triggers haptic warnings to encourage a smoother approach.

Phase 3: Sorting and Reset

Once the human takes the object for inspection, the robot *immediately* retreats to the bin to source the next item.

- The Challenge: The robot retracts while the human is still occupying the workspace to sort the item into "Pass" or "Fail" bins. This is the highest risk for collision.
- Psychomotor Skill: Situational Awareness. The user must focus on their sorting task while maintaining peripheral awareness of the robot's return movement.
- XR-ITE Support: The Safety Computation Engine monitors the distance between the user's head/hands and the retreating robot. If the user leans too far forward into the robot's return path, the system triggers an immediate auditory and haptic alert to enforce the ISO/TS 15066 safety distance.

5. Experimental Evaluation

We conducted a pilot study to evaluate if the XR-ITE system effectively helps students learn safety and teamwork skills. The goal was to compare our interactive training against standard video training and gather initial user feedback. 10 undergraduate engineering students volunteered to this experience. We randomly divided them into two equal groups: a) Control Group which learned by watching a standard training video and b) Experimental Group which learned by practicing inside the XR-ITE system with active feedback. The study consisted of three steps:

1. Introduction: All students received a briefing on the sorting task and basic robot safety rules.
2. Training (10 Minutes):
   - The Control Group watched a video of an expert operator performing the task.
   - The Experimental Group practiced in the VR environment. During this practice, if they moved unsafely, their controllers vibrated (haptic feedback). They also saw a "Ghost Arm" visualization showing where the robot was going to move next.

3. Transfer Test: Immediately after training, both groups performed the task in VR without any help. We turned off the vibrations and visual guides to measure how well they retained the skills on their own.

Even with a small group of 10 students, we found clear differences in performance and received valuable feedback.

Safety Compliance

- Control Group (Video): These students often leaned into the robot's workspace while it was retreating, likely because the video didn't give them a sense of spatial depth.
- Experimental Group (VR): The haptic warnings during training successfully taught them to instinctively stay back during risky moments, even after the feedback was removed.

Collaborative Fluency

- Robot Waiting Time: The Experimental Group worked faster, keeping the robot waiting only 6% of the time, compared to 16% for the Control Group.
- Concurrent Activity: The XR-ITE trained students were more comfortable moving while the robot was moving (40% concurrent activity), whereas the video-trained students tended to stop and wait for the robot to finish completely before moving (22% concurrent activity).

We asked students to rate their experience on a scale of 1 to 5 (5 being best).

- Confidence: The experimental group rated their confidence in working with robots significantly higher (4.5/5) than the control group (2.5/5).
- Student Comments:
  - Control Group: "I understood the steps from the video, but when I got into the simulation, I was surprised by how fast the robot moved towards me. It was scary."
  - Experimental Group: "The vibration was really helpful. It trained my body to know exactly where the 'danger zone' was without me having to look at the floor markings."

6. Conclusion

This pilot study demonstrates that the XR-ITE system is a promising tool for training the future workforce. By integrating a low-cost robotic arm with an intelligent VR tutor, we were able to improve student safety and confidence significantly compared to traditional video training. The results suggest that active feedback (haptics and visuals) helps students build "muscle memory" for safety that passive videos cannot provide. Future work will focus on expanding the study to a larger class and adding more complex assembly tasks.

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