A Multiple Intelligent-Enabled Cognitive Agent Interaction Architecture for Enhancing Student Performance

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ABSTRACT

Designing an effective Learning Management System (LMS) improves the overall teaching and learning performance of students. However, assessing student behavior on a virtual learning platform is difficult, as different students exhibit different contextual behaviors. Multiple Intelligence (MI) combined with Cognitive Architecture (CA) can be adopted to learn these multiple behaviors exhibited by students and improve the overall student experience. MICA-based models exhibit high training time and lower accuracy, thus necessitating the need to improve the learning layer with enhanced agent interaction and rewarding mechanisms leveraging a Deep Reinforcement Learning (DRL) model. An experiment was conducted on the Education Process Mining (EPM) dataset, and the results show that the proposed MICA DRL (MICA-DRL) model exhibited enhanced performance, achieving 99.71% accuracy, which is higher compared to current student performance analysis methods.

Keywords-behavior; cognitive architecture; deep reinforcement learning; multiple intelligence; student performance

I. INTRODUCTION

The integration of Artificial Intelligence (AI) into education has opened new paths for personalized learning and intelligent tutoring systems [1]. One of the pivotal frameworks supporting this personalized approach is Howard Gardner's Theory of Multiple Intelligences (MI), developed in 1983. Gardner challenged traditional views by proposing that intelligence is not a single general ability measurable solely through IQ tests, but rather a set of multiple distinct modalities through which individuals process information and solve problems [2, 3]. Each person possesses unique combinations and varying degrees of these intelligences, a conceptual shift that has had profound implications for education by advocating for more individualized and inclusive teaching methodologies.

Complementing MI theory are cognitive theories that examine how people acquire, process, and store information. Jean Piaget's cognitive developmental theory [4, 5] emphasized that cognitive growth occurs in stages, from sensorimotor to formal operational, each characterized by distinct ways of thinking and understanding the world. The cognitive model highlights the interrelation of thoughts, emotions, bodily sensations, and behavior, illustrating how interpretations of situations influence emotional responses and actions [4]. More recent developments, such as information-processing theory, conceptualize the human mind as a computer system, with intelligence derived from the efficiency of processes such as attention, memory, and reasoning [6].

The convergence of MI and cognitive theories provides a comprehensive framework for understanding human learning and behavior. For example, logical-mathematical intelligence is closely aligned with analytical reasoning processes, while interpersonal intelligence is connected to emotional cognition and social understanding [7, 8]. These alignments suggest that integrating cognitive models into education can better address the diverse intelligence profiles of students. Modern cognitive architectures, such as ACT-R [9] and SOAR [10], model these processes, replicating human-like reasoning and behavior in synthetic agents. This synergy is particularly valuable in AI-driven educational tools, where agents designed within cognitive frameworks can adapt to MI theory, thus supporting diverse learning styles and enhancing student engagement [11]. By incorporating Machine Learning (ML) into these architectures, synthetic agents can dynamically adapt to the cognitive and intelligence profiles of learners [12-15].

The evolution of cognitive architectures demonstrates their growing sophistication. In the 1960s, the General Problem Solver (GPS) [16, 17] modeled problem-solving aligned with logical-mathematical intelligence. This was followed by OPS5 in the 1970s, which improved the modeling of linguistic and interpersonal intelligences through production-rule systems [18]. In the 1980s, connectionist models, such as Parallel Distributed Processing (PDP) [19], and symbolic architectures, such as SOAR [10], were introduced, enabling simulations of bodily-kinesthetic and musical intelligences. In the 1990s, ACT-R [20] and CLARION [21] advanced the representation of declarative and procedural knowledge, strengthening the modeling of intrapersonal and interpersonal intelligence. In the 2000s, architectures such as LIDA [22] and Psi-based Coprime [23] integrated embodied cognition—linking perception, action, memory, and emotion—making them effective for naturalistic and existential intelligences. In the 2010s, neurocognitive architectures such as SPAUN [24], combined with Deep Learning (DL) [25, 26], excelled in tasks that require spatial and linguistic intelligence, enabling intelligent educational agents with personalized interactive capabilities. The current decade continues this trend, incorporating Reinforcement Learning (RL) and domain-specific cognitive models for increasingly individualized education [27, 28].

Empirical studies further demonstrate these applications. In [29], cognitive architectures were compared in e-learning, highlighting their effectiveness in collaborative settings. In [30], a robot behavior management framework used ML methods to assess student engagement. In [31], ML models were used to predict academic performance, refining the results with ensemble bagging techniques and datasets such as DEEDS [32, 33]. In [34], the Interactive Constructive Active-Passive Disengage (ICAPD) model linked student behavior with cognitive engagement, achieving 84% accuracy in predictions using DL. The study in [35] examined how MI-inspired cognitive agents can foster educational interactions through man-machine symbiosis and dialectic learning. In summary, integrating MI theory with cognitive architectures and ML provides a robust path toward intelligent, adaptive educational systems. By tailoring learning experiences to individual cognitive and intelligence profiles, these systems foster deeper engagement and improved outcomes.

This work:

- Proposes a novel Multiple-Intelligence Cognitive Architecture using Deep Reinforcement Learning (MICA-DRL) for adaptive teaching and learning. This work models student behavior using multi-agent cognitive layers: reflexive, reactive, deliberative, and learning agents.
- Incorporates Deep Q-Reinforcement Learning (DQRL) to optimize decision-making and improve student learning outcomes. In addition, it leverages Learning Management System (LMS) interaction data (keystrokes, clicks, content access) to model cognitive engagement and intelligence types.
- Implements a hierarchical multi-agent interaction model to enhance planning, feedback, and personalized instruction. In addition, it formulates learning as a Markov Decision Process (MDP) to handle uncertainty in student behavior.

In practical deployment, MICA-DRL, integrated into LMS, analyzes student interactions to deliver adaptive feedback. It supports instructors by identifying at-risk learners, recommending interventions, and suggesting resources, while personalizing content, paths, and feedback for students. This fosters engagement, enables timely instructional decisions, and bridges theoretical modeling with practical educational impact.

II. METHODOLOGY

MICA-DRL is a novel cognitive architecture that integrates synthetic agents to enhance classroom learning. Using LMS data, such as keystrokes, mouse interactions, visual and mathematical features, it models multiple intelligences to identify strong and weak learners. The architecture adapts instruction, improving performance through personalized and intelligence-driven teaching strategies in virtual environments.

A. *Cognitive Architecture for Enhancing Teaching and Learning*

In the MICA-DRL approach, the mind is modeled as a collection of agents distributed across multiple cognitive layers. These agents work collaboratively to cover critical aspects of cognition and learning. The architecture comprises four core layers—learning, deliberative, reactive, and reflexive—each with specific roles in modeling agent behavior.

Figure 1 presents the MICA-DRL cognitive architecture, detailing the interaction between various agent layers, such as perception, affect, cognition, motivation, and intention. The process begins with a perceptual agent that gathers behavioral and interaction data from the environment. Reflexive Finite State Machine (FSM) agents provide immediate low-level responses, while reactive agents interpret these using BDI (Belief, Desire, Intention) principles for more coordinated actions. Deliberative agents plan goal-oriented strategies, and the Deep Q-Learner in the learning layer optimizes decisions through RL. Meta-cognitive agents (MetaBelief, Meta-I) oversee adaptation and strategy refinement. This layered coordination enables dynamic, personalized interventions, enhancing teaching and learning outcomes based on student behavior patterns.

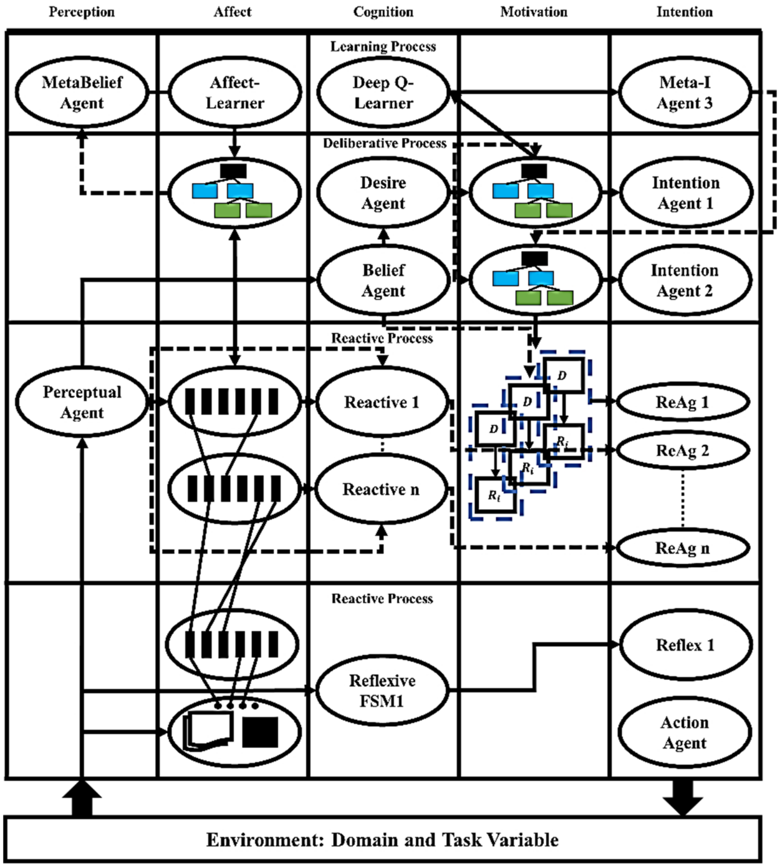

Fig. 1. MICA-DRL architecture for improving the overall teaching and learning experience of students.

In MICA-DRL, consider E as an environment that consists of domain and task variables. O_t denotes the environment at time t, A_t denotes the action taken by the agent at t, R_t denotes the reward received at t, S_t denotes agent-state at t, π denotes policy function-mapping states for actions, i.e., $\pi: S \rightarrow A$, $V^{\pi}(s)$ denotes the value function for policy π, $Q^{\pi}(s,a)$ denotes the action-value function for the policy π, γ denotes the discount factor for future rewards, i.e., $\gamma \in [0,1]$, and α denotes the learning rate. The agent layers are the reflexive layer $\mathcal{R}_f = \{RF_i\}_{i=1}^{m}$, the reactive layer $\mathcal{R}_x = \{RX_i\}_{i=1}^{n}$, the deliberative layer $\mathcal{D} = \{DA_i\}_{i=1}^{p}$, and the learning-layer $\mathcal{L} = \{LA\}_{i=1}^{q}$. The whole system is modeled as a Markov Decision Process (MDP) due to uncertainty in student behavior patterns. The MICA-DRL environment E can be defined as:

$$E = (S, A, T, R, \gamma) \qquad (1)$$

where S denotes a set of states (performance indicators, engagement levels, and student knowledge states), A denotes a set of actions (content delivery, recommendation, and feedback), $T: S \times A \times S \rightarrow [0,1]$ denotes the transition function, i.e., the probability of a state transition using action a, $R: S \times A \rightarrow \mathbb{R}$ denotes the reward function, and γ denotes the discount factor.

B. *Reflexive Layer*

This is the initial layer and the lowest level of the proposed MICA-DRL architecture, where small and simple agents exist, showing simple behavior. The agents provide output using a function (perception) for any input. The output is always in the form of a behavioral action. The agents in the reflexive layer are termed reflexive-agents. Each reflexive agent has to follow the architectural rules (constraints). For every output, the reflexive agent changes its location (goes to the next level) only if it provides output; otherwise, it changes its location diagonally (i.e., right, left, back, front). The reflexive agents provide output on the basis of instincts and perception, which helps them to move around the architectural locations. Consider a reflexive agent $RF_i \in \mathcal{R}_f$ modeled as a finite-state machine:

$$RF_i = (Z_i, \Sigma_i, \delta_i, z_{0,i}, O_i) \qquad (2)$$

where Z_i denotes the internal states set, Σ_i denotes the input set from the environment (e.g., keypresses, mouse clicks), $\delta_i: Z_i \times \Sigma_i \rightarrow Z_i$ denotes the state transition function, $z_{0,i}$ denotes the initial state, and $O_i: Z_i \rightarrow A$ denotes the output function producing an action. These agents move to the next layer if $O_i \neq \emptyset$; else, they follow diagonal transitions.

C. Reactive Layer

This is the second layer of the MICA-DRL architecture. The agents in the reactive layer are termed reactive-agents. This layer performs various tasks based on the reflexive agents' output, due to which reactive agents display harmonized and organized exertion. The reactive agents are administered using the BDI agent. Reactive agents react based on internal beliefs, desires, and intentions. Each $RX_j \in \mathcal{R}_x$ is modeled as:

$$RX_j = \left(B_j, D_j, I_j, \phi_j\right) \tag{3}$$

where B_j denotes beliefs (information from reflexive outputs), D_j denotes desires (objectives or goals), I_j denotes intentions (committed plans) and ϕ_j denotes a function to determine an action $\phi_j\left(B_j, D_j, I_j\right) \to A$. Reactive agents select action $a \in A$ based on:

$$a = \arg\max_{a'} Q^{\pi}(S_t, a') \tag{4}$$

D. Deliberative-Layer

This is the third layer of the MICA-DRL architecture, having BDI agents. The BDI agents use certain reactive agents and reflexive agents for completing assigned tasks (input). Deliberative agents $DA_k \in \mathcal{D}$ use planning algorithms to fulfill goals. They plan over a longer horizon, using the output of RX_j and combining plans using:

$$DA_k = (P_k, \Theta_k, \rho_k) \tag{5}$$

where P_k denotes a set of plans, Θ_k denotes planning constraints and $\rho_k: (S_t, G_t) \to P_k$ denotes the planning function, selecting a plan to achieve a goal G_t. The plans are a sequence of actions:

$$P_k = \{a_1, a_2, \dots, a_T\} \tag{6}$$

The agent uses model-based RL for planning under uncertainty.

E. Learning Layer (DQRL)

This is the last layer of the proposed DQRL-based MICA-DRL architecture, which utilizes the initial, second, and third layers for learning how the task has been executed. This layer combines the meta-cognition layer and meta-control layer. The agents in the learning layer are termed learning-agents. The learning agents utilize the proposed DQRL algorithm to learn to execute different tasks (input). The DQRL algorithm utilizes a rewarding approach for learning. The DQRL uses policy and value to give a reward for every completed task. The DQL approximates the action-value function $Q(s, a)$ using a neural network $Q(s, a: \theta)$, with parameter θ. The Q-learning update rule is given as:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right] \tag{7}$$

In DQRL, this is carried out using a Deep Neural Network, as:

$$\mathcal{L}(\theta) = \mathbb{E}_{(s,a,r,s')\sim D}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta)\right)^2\right] \tag{8}$$

where D denotes the experience replay buffer and θ^- denotes target network parameters (which are updated periodically). In this work, the policy is derived using:

$$\pi(s) = \arg\max_{a'} Q(s, a; \theta) \tag{9}$$

F. Reward Mechanism

Each action a taken in the state s receives a reward, which is represented as:

$$R(s, a) = \begin{cases} +1, & \text{if action improves learning} \\ 0, & \text{if neutral effect} \\ -1, & \text{if detimental} \end{cases} \tag{10}$$

The DQRL agent uses both policy $\pi(s)$ for deciding which action to take and the value function $V(s) = \max_a Q(s, a)$ for evaluating state quality.

G. Multi-Agent Interaction Model

The overall system can be viewed as a multi-agent hierarchical RL system. Let $\mathcal{A} = \left\{RF_i, RX_j, DA_k, LA_l\right\}$ be a set of all agents. Each agent $a_i \in \mathcal{A}$ interacts in a hierarchy based on its level, i.e., $RF_i \to RX_j \to DA_k \to LA_l$. The transitions are governed by communication functions, defined as:

$$\begin{aligned} &T_{i\to j}: O_{RF_i} \to I_{RX_j}, \forall_{i,j} \\ &T_{j\to k}: O_{RX_j} \to I_{DA_k} \\ &T_{k\to l}: O_{DA_k} \to I_{LA_l} \end{aligned} \tag{11}$$

H. MICA-DRL

The proposed MICA-DRL framework functions through layered agent interactions across cognitive processes. Initially, perceptual agents gather LMS data such as keystrokes, mouse clicks, and content access, forming observations O_t. Reflexive agents RF_i then generate immediate, rule-based responses, forwarding valid outputs to reactive agents RX_j , which interpret actions using the BDI model for goal alignment. Deliberative agents DA_k build structured plans to support engagement and comprehension. Finally, learning agents LA_l employ DQRL to refine decision-making through reward-driven policy updates. This multi-layered design enables adaptive, intelligence-driven responses, dynamically enhancing student learning and performance in virtual educational environments.

The core objective of the MICA-DRL system is to maximize the cumulative reward received during the learning sessions. This is formally expressed as:

$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R\left(s_t, \pi(s_t)\right)\right] \tag{12}$$

where π represents the policy function that maps states to actions, $R\left(s_t, \pi(s_t)\right)$ is the reward received after taking an action at state s_t, γ denotes the discount factor indicating the importance of future rewards, and the expectation is taken over all possible state-action sequences. The goal is to continuously improve this policy through learning, ensuring that each agent in the architecture contributes to enhancing the student's overall learning experience and academic performance.

III. RESULTS AND DISCUSSION

This classification performance of MICA-DRL was compared against existing student assessment models, including Multi-Split Feature-Aware (MSFA) [33], Random Forest-based Hybrid-Classifier (RFHC) [36], Feature-Aware Decision-Tree (FADT) [37], and an XGB-based [38]. Experiments were conducted using the Educational Process Mining (EPM) dataset from the UCI Machine Learning Repository [39]. The dataset comprises behavioral logs collected from 115 students participating in a virtual learning environment in six independent session streams. Each stream records detailed interaction data, including keystrokes, mouse clicks, and navigation actions, which together capture diverse patterns of student engagement. These logs provide a valuable resource for modeling learner behaviors and linking them to academic performance outcomes.

Data were split into 70% training and 30% testing. To ensure reliability and consistency, several preprocessing steps were applied. First, categorical variables, such as session identifiers, were transformed into numerical representations using one-hot encoding. Continuous variables, including assessment scores and task completion times, were normalized to the [0,1] range to prevent scale dominance. Records from incomplete sessions containing fewer than 10 logged events were excluded, resulting in 31,450 valid interaction events for analysis. To support robust evaluation, a 5-fold stratified cross-validation strategy was adopted, preserving the balance between strong and weak learner classes in each fold. MICA-DRL was configured with a learning rate of 0.001, a discount factor $\gamma = 0.95$, 1,000 epochs, *batch size* = 64, and *replay_buffer* = 10,000. Training employed TensorFlow 2.12 and scikit-learn 1.2.2 on an RTX 3080 GPU system. To mitigate overfitting, early stopping, dropout (0.3), and 5-fold cross-validation were applied. From the raw logs, a set of derived features was calculated to capture learning behavior. These features were selected to reflect engagement, consistency, and progression.

The feature extraction process derived key indicators of student behavior from raw interaction logs to support accurate performance modeling. The keystroke frequency was defined as the average number of keyboard inputs per session, while the mouse click rate measured clicks per minute, reflecting the intensity of interaction. Navigation depth captured unique content transitions, showing exploration patterns, and time-on-task quantified the average duration per activity as a proxy for engagement. The frequency of content access indicated revisits to resources, suggesting reinforcement or difficulty, while the consistency of engagement (standard deviation of time-on-task) highlighted the stability of focus. Finally, the progression pattern measured the adherence to suggested activity sequences. Each student's interaction history was aggregated into a structured feature matrix, forming the input for MICA-DRL and baselines, ensuring reproducibility and transparent mapping from behaviors to predictive outcomes. Performance was assessed using accuracy, precision, recall, and F-score:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{13}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{14}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{15}$$

$$\text{F} - \text{score} = \frac{2*\text{Precision}*\text{Sensitivity}}{\text{Precision}*\text{Sensitivity}} \tag{16}$$

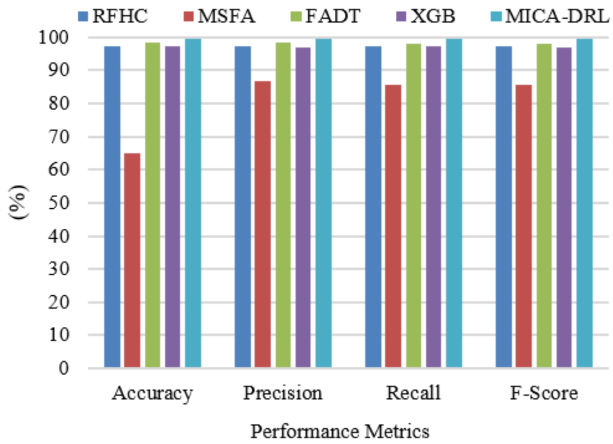

Fig. 2. Performance evaluation results in assessing student performance using session activity.

The results show that MSFA performed the weakest (65% accuracy), while FADT achieved 98.28% accuracy. MICA-DRL outperformed all, achieving 99.71% accuracy, 99.7% precision, 99.7% recall, and 99.68% F1-score, confirming its superior predictive power and potential for personalized learning support. A 5-fold cross-validation on the EPM dataset showed minimal variability in MICA-DRL's performance. Specifically, the standard deviation across folds was ±0.12% for accuracy, ±0.15% for precision, ±0.14% for recall, and ±0.16% for F1-score. These low deviations indicate that MICA-DRL consistently delivers strong predictive performance, reinforcing the reliability of the reported results.

IV. CONCLUSION

This study examined different MI and CA approaches, highlighting their significance and limitations in adapting to the student domain. It also emphasized that the current MICA and its enhanced model have not been explored for assessing student performance. The proposed MICA-DRL framework improved the learning layer with enhanced agent interaction and reward mechanisms leveraging DRL, and experiments on the EPM dataset demonstrated superior performance in terms of accuracy, precision, recall, and F-measure compared to existing methods. However, this study is limited by the relatively small size of the dataset and the dependence on a single publicly available source, which may affect generalizability. Future work will focus on validating MICA-DRL with larger and more diverse datasets across different educational contexts, integrating multimodal data such as speech and facial cues, and exploring explainable AI techniques to enhance interpretability for educators. These directions will strengthen the robustness, scalability, and practical utility of the proposed framework.

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