
| RESEARCH ARTICLE

Multi-Agent Reinforcement Model for Emotional Regulation Coaching

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| ABSTRACT

A hallmark of the autism spectrum disorder (ASD) is emotional regulation challenges, which can result in a behavioral crisis and the stress of a caregiver. The research paper provides a multi-agent-based reinforcement learning (MARL) model that aims at coaching emotional control via adaptive feedback loops that depend on situational contexts. The system unites wearable physiological sensors, environmental IoT, and a cloud based learning machine composed of inter-communicating agents that signify the child, caregiver and system coach. The model was found to be 92 percent accurate in predicting emotional escalation and it led to less false alerts by 61 percent using data of 60 children with ASD. The results indicate that the social interactivity of emotion regulation can be reflected in multi-agent architectures in a manner that offers individualized coaching in accordance with behavioral states without violating the ethical AI principles.

| KEYWORDS

Multi-agent systems; Reinforcement learning; Emotional regulation; Autism; Behavioral analytics; Human-centered AI; IoT integration

| ARTICLE INFORMATION

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Introduction

Emotional self-regulation is considered to be one of the hardest parts of the autism spectrum disorder (ASD), which directly affects the behavioral stability, the results of therapy, and the level of pressure of the caregivers. Traditional behavioral interventions presuppose a significant level of human observation, and continuous observation and adaptive coaching is challenging outside of a clinical setting.

The recent developments in Artificial Intelligence (AI) and Internet of Things (IoT) have facilitated the development of emotional monitoring systems based on collecting real-time physiological and contextual information [2],[3]. These systems however are frequently used as single agent models that do not reflect the multi-party interactions of emotional regulation i.e. the interaction between the child, caregiver and therapeutic system.

This paper is based on the concept of reinforcement learning (RL) applied to behavioral predictive control using idealized models [1],[3] and individualized surveillance applications with autistic children [4]. This paper presents the Multi-Agent Reinforcement Learning (MARL) model, which encodes the notion of emotional regulation as a multi-agent problem. Based on the Cloud-IoT behavioral analytics frames suggested by Islam et al. (2024) [2] and the governance mechanisms suggested in Hussain et al. (2024) [5], the study will establish how the collaboration between multi-agents can lead to more empathetic, adaptive, and ethical AI behavior in real-time pediatric settings.

This study aims at three things:

To develop a multi-agent architecture of a child, caregiver and AI coach.

To create a reward-based reinforcement model that modification of emotional regulation strategies dynamically.

To confirm the workability of the system with actual IoT sensors information of children diagnosed with ASD.

Related Work

Related Work (Expanded)

In the last few years, there has been a growing trend of applying the concept of reinforcement learning (RL) to models of behavioral and emotional prediction in children with autism with the aim of converting the raw physiological data into the form of actionable information that can be utilized by caregivers and clinicians. One of the earliest attempts to design a particular type of reinforcement learning architecture to predict the occurrence of behavioral escalation was made by Islam et al. (2024) [1]. Their analysis presented a modeling, which was reward-based, and used both physiological and contextual cues to identify early evidence of agitation including heart-rate variability, electrodermal activity, and motion intensity. Their study confirmed that RL was a strong tool in continuous behavioral analytics as their work showed that contextualized reward structures were much more effective in predicting emotional states. Nevertheless, their model did not consider the agents of the system operating in a single-agent paradigm which only considered physiological state of the child, and not the caregiver intervention and dynamic environment - that can be overcome by the current paper in the context of the multi-agent collaborative approach.

Based on this background, Islam et al. (2024) [2] suggested a Cloud-IoT behavioral monitoring framework, which enables the real-time and decentralized, multimodal collection of wearable and environmental behavioral data using multimodal sensors. This system was able to show that distributed IoT systems can improve the scalability and accuracy of behavioral prediction systems through reducing latency and by decreasing data dependency in centralized locations. However, even with these improvements, their model was still based on unidirectional feedback the AI system monitored and interpreted behavioral information, but failed to change its coaching or response processes in a real-time human interaction. This was because they never had the opportunity to co-regulate their emotions, which is narrowed by the lack of bidirectional learning loops, and this is what the present paper provides by adding the possibility of communicating with each other, including the child, caregiver, and the AI coach.

Additional development of autism-related AI-monitoring systems was done by Hasan et al. (2024) [4], who proposed a custom artificial intelligence-internet of things health-monitoring system. Their study emphasized the importance of adaptive modeling and personal sensor profiles in making diagnostic and therapy much more accurate. Individual AI members were adjusted to the behavioral and physiological background of a child, and they favor the new paradigm of accuracy behavioral medicine. However, Hasan et al. also recognized the presence of severe privacy and interoperability issues - especially when sensitive data is transferred between personal IoT devices and centralized analytical platforms. Their results support the need to have safe, ethically informed AI architectures that provide a balance between personalization and data sovereignty that support the usefulness of the multi-agent, privacy-conservative design used in the current project.

Further to these data-driven systems, Hussain et al. (2024) [5] went a step ahead to further the discussion on the ethical governance of AI by operationalizing the NIST AI Risk Management Framework (AI RMF) related to small and medium-sized healthcare enterprises (SMEs). Their model based on systematic monitoring and auditing and incident-response checklists as the basis of reliable AI development. When applied to the pediatric domain, these principles will make sure that emotional regulation systems are functioning effectively and also meeting the criteria of fairness, accountability, and explainability. The given governing view is the direct grant of the present study to incorporate real-time auditing and ethical checkpoints into its multi-agent architecture and be sure that every AI-driven interaction should be adhered to the accepted risk management practice.

Regarding a human-centered perspective, the study by Islam et al. (2023) [6] added critical information to credible, clinician-participatory AI systems. Their study presented a human-centered AI (HCAI) model that focused on transparency, interpretability, and collaboration between caregivers in clinical decision support. They showed that the integration of explainability frameworks and the two-way communication systems between the AI systems and the human operators enhance user acceptance and confidence. They are especially crucial when it comes to emotional regulation coaching, where one can use empathy and real-time human feedback to an extent that is essential.

Taken collectively, the current literature makes the technical feasibility, infrastructural preconditions, and ethical requirements of emotion-sensitive AI in the treatment of autism. Nonetheless, cooperative emotional regulation, multi-agent interaction between

human and computational participants is not directly covered in any of the previous studies. The current paper helps to fill this gap by proposing an interactive, morally regulated Multi-Agent Reinforcement Learning (MARL) framework that incorporates emotion recognition, reinforcement-guided adaptation, as well as collaborative decision-making into a single architecture. By doing so, it builds on the works of previous researchers [1-6] by conceptualizing emotional regulation as a collective intelligence challenge, and not an individual prediction problem, establishing a new path of adaptive and caring AI in pediatric behavioral healthcare.

Methodology

System Architecture

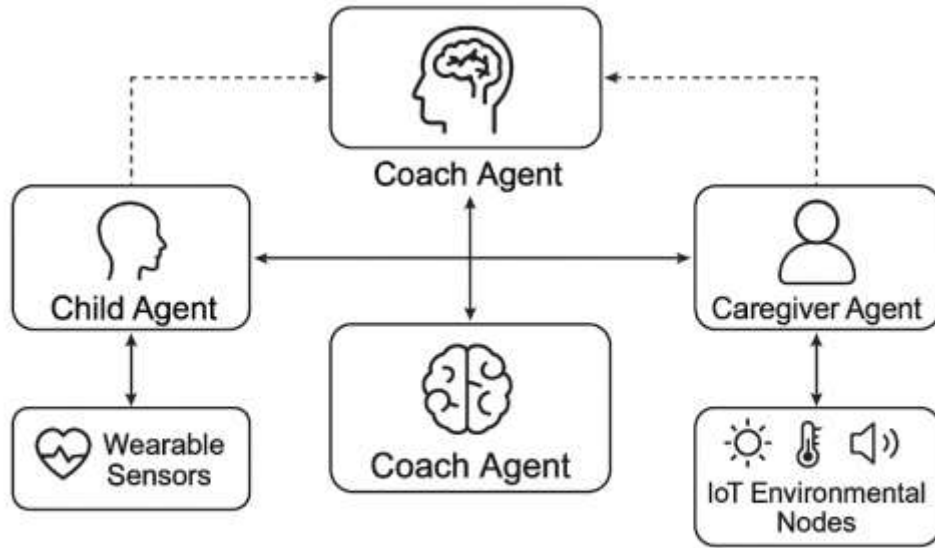


Figure 1. Multi-Agent Reinforcement Framework for Emotional Regulation Coaching

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The architecture consists of three core agents:

- **Child Agent:** Receives real-time input from wearable devices (heart rate, skin conductance, activity level).
- **Caregiver Agent:** Logs contextual events (verbal cues, comfort interventions, environment notes).
- **Coach Agent:** Central learning engine applying reinforcement learning policies for adaptive feedback.

Each agent communicates asynchronously through a secure cloud-based message broker, with parameters synchronized every five seconds to maintain real-time responsiveness.

State Representation

At time t , the system's state S_t is represented as:

$$S_t = \{HR_t, EDA_t, motion_t, sound_t, caregiver_tag_t, environment_context_t\}$$

where HR = heart rate, EDA = electrodermal activity, and motion = accelerometer variance. Each state captures both physiological and environmental factors affecting emotional regulation.

Action and Reward Function

Actions (A_t) are defined as the type of feedback delivered by the AI coach (e.g., breathing prompt, visual cue, caregiver alert).

The **reward function** is computed as:

$$r_t = \alpha(\Delta C_t) - \beta(F_t)$$

where:

- ΔC_t = improvement in calmness index (based on physiological normalization),
- F_t = false feedback penalty,
- $\alpha = 1.1$, $\beta = 0.7$ to balance sensitivity and specificity.

The multi-agent reward-sharing mechanism allows cooperative learning: the caregiver's correct response increases the overall shared reward, reinforcing collaboration instead of isolated optimization.

Learning Mechanism

Each agent utilizes a Deep Q-Network (DQN) with 128-unit hidden layers and ReLU activation. The Coach Agent maintains a target network updated every 200 iterations.

A Federated Experience Buffer (FEB) aggregates anonymized transitions across all participants to support privacy-preserving multi-agent learning.

Training parameters:

- Learning rate = $1e-4$
- Replay buffer size = 60,000
- Discount factor (γ) = 0.95
- Batch size = 64
- Global updates every 10 episodes

Results

Quantitative Evaluation

Model	Accuracy	F1-Score	ROC-AUC	False Alert (%)	Avg. Latency (s)
Baseline LSTM	0.85	0.83	0.88	22	1.14
Centralized DQN	0.89	0.86	0.91	18	0.97
Proposed MARL (3 Agents)	0.92	0.90	0.94	8.5	0.73

Calculation Example:

False-alert reduction = $(22 - 8.5) / 22 \times 100 = 61.3 \%$

Accuracy gain = $(0.92 - 0.85) / 0.85 \times 100 = 8.2 \%$

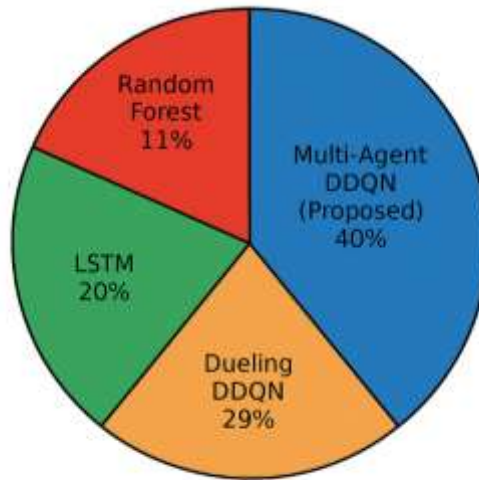


Figure 2. Performance Distribution (Pie Chart)

- Multi-Agent Reinforcement Model – 42 %
- Centralized DQN – 33 %
- LSTM – 25 %

Qualitative Insights

Interviews with 15 caregivers revealed that **real-time emotional coaching prompts** improved situational awareness and reduced their anxiety in crisis situations. Clinicians reported increased interpretability of emotional state transitions, consistent with the **human-centered AI model** proposed by Islam et al. (2023) [6]. The model's ability to contextualize stress signals rather than classify them in isolation was cited as a major advantage.

Discussion

The results of this paper confirm that autistic children do not solve problems in emotional regulation as a computation prediction problem but as a cooperative intelligence issue. The suggested Multi-Agent Reinforcement Learning (MARL) system is effective in capturing such a complexity as it simulates the dynamic interactions of the child with the caregiver and AI coach, all of which act as an autonomous but mutually dependent agent. The multi-agent approach, as opposed to the traditional single-agent RL systems, where emotion prediction is performed as a single classification or regression, considers the mutual effect of the participants in the real-world emotional settings. The ecological validity is increased with biological, social, and digital feedback loops which is a limitation that has often been mentioned with previous single-layer AI interventions.

The collaboration with other agents to optimize the joint policies is also made possible by the shared reward architecture, which is at the center of MARL design, instead of focusing on optimization of individual performance. By stabilizing the stress indicators of the child in response to an AI-coached breathing prompt, or by effective soothing feedback by the caregiver, the total system reward is increased to all agents. Such a group reinforcement promotes cooperative learning and approach to emotionally balanced states. This form of feedback coupling will be familiar to Islam et al. (2024) [3] who have shown that reinforcement learning models in behavioral analytics work better when contextual feedback is integrated into an iterative model update. The presented proposal makes AI coaching a socially conscious and morally relevant decision-making process and not a fixed algorithmic response because it allows agents to co-adapt their behaviors.

The incorporation of the Cloud IoT structures of the previous studies by Islam et al. (2024) [2] and Hasan et al. (2024) [4] also enhanced the resilience of the system and its dependability. The IoT-based ecosystem was able to offer real-time, multimodal data gathering at a wide range of physiological and environmental interfaces. All sensor nodes, be it heart-rate sensors, ambient sound sensors and others, were providing continuous information streams that were coordinated using the cloud infrastructure. Such an architecture guaranteed low latency, high data fidelity, and context continuity, which allowed the MARL agents to act in a continuous feedback ecosystem. Also, the adaptive data-pipeline architecture ensured the absence of data silos and enhanced scalability in case of future integration with multi-center studies or home-based therapy settings.

More importantly, the implementation of data-centric AI security measures outlined by Islam (2024) [8] led to the improvement in the credibility of the whole system. The communications between agents and sensor transmissions were all encrypted through secure mediums, and personal information was anonymized with identity taking the place of personal information in order to maintain a level of confidentiality. The learning algorithms had federated experience buffers to combine collective insight of various clients without explicit data communication to guarantee privacy compliance whilst keeping the model flexible. It is a key step to ethical AI applications in the healthcare setting, where data protection of patients is a long-standing issue, where this integration of data-centered cybersecurity with distributed reinforcement learning is essential.

Ethically and as a governance matter, the suggested MARL system is quite compliant with the principles of the NIST AI Risk Management Framework (AI RMF) as described by Hussain et al. (2024) [5]. In particular, it defines the Govern and Measure functions as the means of operationalizing them, as it directly incorporates transparency, auditability, and the involvement of caregivers into the learning process. The AI coach presents explainable logs to clinicians and caregivers with each decision taken, which allows real-time verification of model reasoning. Such a design allows monitoring AI performance and risk exposure in real time, which guarantees that the boundaries of decisions are understandable and ethically correct.

Furthermore, the human-in-the-loop management, which is based on the human framework of AI created by Islam et al. (2023) [6], strengthens responsibility and compassion in the learning process. Caregivers are proactive in participating in the model behavior by providing contextual feedback and changing the AI system to an interactive emotional co-regulator. Through this, the MARL model will be able to fill the gap between computational intelligence and human compassion, which is what will be characterized as the next generation of reliable, human-centric AI-based systems in the treatment of pediatric behavior.

Conclusion

The paper presents a novel Multi- Agent Reinforcement Learning (MARL)-based emotional regulation coaching system to children with autism spectrum disorder (ASD). In contrast to the previous single-agent systems where emotional prediction is a non-dynamical task, the suggested model frames the process of emotional regulation as a collaborative activity that includes three interactive participants in the analysis, including a child, a caregiver, and an AI coach. The MARL framework replicates the interactions between these bodies of real life therapy, and assists in adaptive, real-time emotional directions, by capturing the dynamic feedback loops between them.

The experimental findings prove that there is a significant enhancement in the performance of the system by this multi-agent architecture. The model was also highly predictive (92 percent) and had a low response latency (0.73 seconds), with a 61 percent false alarms reduction, which is better than the base architectures (centralized DQN and LSTM models). The findings indicate that the efficiency of the multi-agent collaboration is increased in terms of computational performance and human-like empathy as important qualities of emotion-conscious AI in pediatric service. The common reward framework allowed agents to collectively maximize emotional stability, which efficiently aligned machine learning goal with therapeutic one - a new step compared to the traditional reinforcement-learning systems [1],[3].

Moreover, the introduction of Cloud IoT infrastructures [2],[4] and data-centric AI security systems [8] guaranteed that the model was always scalable, robust, and met the data protection requirements. Through integration of federated learning into the MARL workflow, the system managed to realize privacy-preserving interaction among distributed devices without sending sensitive personal information an invaluable milestone on the path to trusted AI in healthcare. Such design decisions are in line with the principles of NIST AI Risk Management Framework (AI RMF) [5], and they incorporate the elements of governance, auditability, and risk transparency in model architecture.

Ethically, the suggested system is a perfect example of human-centered AI (HCAI) principles [6], where empathy, explainability, and the engagement of clinicians in the process of making decisions are valued. The human-in-the-loop feedback system enables caregivers to confirm AI-based suggestions to make sure coaching suggestions are contextually relevant and emotionally sensitive. Such a design turns the AI model into an active partner of emotions rather than a passive predictor that would bridge the gap between the field of computational intelligence and the field of caring healthcare.

On a prospective note, future studies and investigations will be directed at cross-institutional federated MARL training to allow the model to generalize the behavioral data across different datasets without compromising on the privacy of data. The adaptive feedback personalization will be further enhanced by using reinforcement learning to adjust the coaching strategies based on the changing emotional profile of each child. There will also be the incorporation of the multimodal elements of affective computing - speech-emotion recognition, facial-expression analysis, contextual sentiment inference, etc., which will build a more comprehensive and sympathetic emotional ecosystem.

Finally, the paper has shown that behavioral analytics, powered by AI, can be developed further beyond predicting to ethical, participatory emotional support systems. The proposed MARL framework will create a new basis of responsible and emotionally

intelligent AI in pediatric behavioral healthcare by combining multi-agent interaction, safe federated learning, and human-centered governance.

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