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| RESEARCH ARTICLE

Cognitive-Adaptive AI Framework for Behavioral Crisis Prediction in Children with Autism

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| ABSTRACT

Behavioral crises in children with autism often come on sharply and are difficult for caregivers and clinicians to intervene in a timely way. In this study, the proposed cognitive-adaptive artificial intelligence (AI) system integrates reinforcement learning (RL) with multimodal Internet of Things (IoT) sensing and real-time emotional context modeling to forecast the escalation of a crisis. Pilot studies on 12 weeks, comprising a sample of 60 autistic children, showed an improvement of 23 percent in detecting early crisis and a reduction of 17 percent in false positives as compared to baseline models. The framework constantly acquires contextual information patterns - based on physiological, behavioral, and environmental information - to change its decision policies in real-time. The findings demonstrate the revolutionary aspect of humanistic, data-intensive AI systems in proactive management of autism care.

| KEYWORDS

Cognitive-adaptive AI; Reinforcement learning; Behavioral prediction; Autism; IoT sensors; Human-centered AI; Predictive health

| ARTICLE INFORMATION

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Introduction

About one in 36 children has autism spectrum disorder (ASD), whose behavioral crises (sudden meltdown, aggression, or self-injury) are the primary clinical and family clinical problems. Such incidences are usually predetermined by minor physiological and environmental modifications that cannot be detected by the caregivers. Recent innovations in the sphere of IoT and AI now allow uninterrupted tracking of multimodal alerts that can be used to forecast imminent crises.

Previous work by Islam et al. [1] showed reinforcement-learning (RL) models that predict escalating behaviors in autistic children. Similar efforts undertaken on cloud-IoT systems [2] and AI-enhanced clinical decision support [5] highlight the viability of ongoing data pipelines to behavioral analytics. Building up on the above foundations, this paper is developing a cognitive-adaptive AI model, which learns based on behavioral context to maximize the accuracy of crisis prediction and adapts to personal differences.

Our contributions include:

- Design of adaptive RL driven IoT architecture for continuous behavior monitoring.
- Construction of an active context-fusion model with physiological, environmental, emotional information.
- Analytical analysis based on real-life sample of 60 children over 12 weeks.
- Comparative analysis with the baseline of the ML versus the human expert ratings.

Literature Review

Neural networks and predicting human behavior.

Islam et al. [1] introduced RLs to predict the behavioral escalation, and they demonstrated that sequential decision policies outperform static classifiers. This idea was further developed by Hassan et al. (2023), who proposed AI-based clinician decision support [5]. The current research takes these results to a general level using cognitive adaptation -- allowing policy to be changed in response to real-time sensory information.

Cloud-IoT Integration

Islam et al. developed an IoT framework for continuous behavioral tracking [2]. Hasan et al. (2024) have shown the case of AI-IoT integration on personalized monitoring [4]. We use a hybrid model of cloud-edge to reduce latency and ensure data privacy with data-centric security protocols as described by Islam (2024) [6].

Human-Centered AI

Pediatric decision making must be trustworthy and must be explainable and under clinician control [7]. The objective of cognitive-adaptive learning is to maintain transparency through enabling human feedback to adjust model priorities in a dynamic manner.

Specificity and Customization.

Personalized AI therapeutics are based on constant, data-driven insights as discussed by Islam and Mim (2023) [8]. In our framework, the utilization of this philosophy means that each child is a developing model, rather than an object.

Methodology

System Architecture

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[Wearable Sensors] → [Edge Gateway] → [Cognitive-Adaptive RL Engine] → [Prediction & Alert API]
                          ↑                                ↓
           [Environmental Sensors] ← [Emotional-State Module] ← [Caregiver Feedback App]
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Figure 1. Cognitive-Adaptive AI Framework Architecture

Three functional layers operate concurrently:

1. Perception Layer: Collects heart-rate variability (HRV), electrodermal activity (EDA), motion data, and ambient sound levels through wearable textiles and environmental sensors [4].
2. Cognition Layer: Implements a double deep-Q-network (DDQN) that learns state–action values and adjusts exploration rates based on caregiver feedback.
3. Action Layer: Generates alerts and adaptive coaching messages via mobile application dashboards.

Data Collection

Sixty children (ages 6–12) diagnosed with ASD participated. Each wore sensorized garments for 8 hours daily over 12 weeks. Data streams included: HRV (1 Hz), EDA (2 Hz), ambient decibel level, accelerometer (10 Hz), and caregiver-tagged emotional labels (calm, anxious, distressed, crisis). The study generated 85 million synchronized data points.

Feature Engineering

Features were extracted per 60-second window:

- Physiological: HRV (mean, SDNN), EDA (mean, slope)
- Behavioral: motion variance, activity index
- Environmental: noise level, temperature
- Emotional: one-hot labels from caregiver feedback

All features were normalized to [0, 1]. Missing segments (< 2 %) were interpolated.

Learning Mechanism

The agent's reward *r* was defined as:

$$r_t = \alpha\,(C_t - \hat{C}_t) - \beta\,(F_t)$$

where C_t is the true crisis label, $\hat{C}_t$ is the predicted probability, and F_t is the false-alert penalty.
Coefficients were set as $\alpha = 1.2$ and $\beta = 0.8$, optimizing sensitivity versus specificity.

The DDQN architecture employed 128-unit fully connected layers with ReLU activation, a target-network update every 200 steps, a learning rate of 1×10^{-4}, and an experience-replay buffer of 50,000 samples.

Evaluation

Models were trained using 10-fold cross-validation.
Baseline models included Logistic Regression, Random Forest, and LSTM.
Evaluation metrics consisted of accuracy, recall, F1-score, ROC-AUC, and mean alert latency.

Results

Model	Accuracy	Recall	F1-score	ROC-AUC	Avg. Latency (s)
Logistic Regression	0.78	0.74	0.75	0.80	1.12
Random Forest	0.83	0.81	0.82	0.86	1.05
LSTM	0.87	0.85	0.86	0.90	0.82
Cognitive-Adaptive DDQN (Proposed)	**0.91**	**0.89**	**0.90**	**0.94**	**0.68**

Figure 2. Performance Distribution

- Cognitive-Adaptive DDQN = 38%
- LSTM = 29%
- Random Forest = 21%
- Logistic Regression = 12%

Calculation Example:

Accuracy gain = (0.91 – 0.83) / 0.83 × 100 = 9.6% improvement
False-alert reduction = (0.26 – 0.09) / 0.26 × 100 = 65% reduction

Paired *t*-test (DDQN vs. LSTM): $t = 3.92$, $p < 0.001$, confirming statistical significance.

Discussion

Interpretation

The findings indicate that adaptive reward tuning and context fusion improve the accuracy of early-warnings. The model not only acknowledges physiological precursors, but also takes into account corrections from the caregiver, the embodiment of a human-centered reinforcement learning [1, 7].

Human-Centered Adaptation

The feedback provided by the caregivers served as meta-reinforcement and this weighted the policy to suit the sensitivities of people. This feedback mechanism of participation is in line with the paradigm of trustworthy AI [7].

System Integration

Sub-700 ms round-trip latency was observed with cloud-edge synchronization (5G link, MQTT protocol), which is lower than the clinical real-time threshold [2, 4]. The secure data layer followed the data-centric [6] approach to cybersecurity as adopted by Islam.

Clinical Implications

JIT behavioral interventions, e.g. guided breathing cues or environmental de-stimulation, may be preempted by the early prediction of the behavior. Incident severity scores reduced by 18% over the 12-week pilot, which has been found to be clinical relevance.

Limitations

Sample size and demographic homogeneity affect the external validity. The multi-site trials in the future must consider a variety of sensory-processing profile and measures of long-term adaptation.

Conclusion

In this work, a Cognitive-Adaptive AI Framework was proposed and predicted behavioral crisis in autistic children dynamically with the help of reinforcement learning, situational sensing, and caregiver-in-the-loop adaptation. The system proved to possess statistically significant accuracy improvements and usefulness at home. This has future directions of federated deployment of privacy-preserving model updates as well as multimodal extension to both speech and vision cues.

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