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Reinforcement Learning Models For Anticipating Escalating Behaviors In Children With Autism

Md Maruful Islam[1] , Md Mehedi Hassan[2] , Md Nayeem Hasan[3] , Sanjida Islam[4] , Abdullah Hill Hussain[5]

[1]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- himul@mimul.com.bd ORCID- https://orcid.org/0009-0009-7819-3096
[2]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- mehedi61@gmail.com Orcid- https://orcid.org/0009-0001-8910-0846
[3]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- mdhasan.student@wust.edu
[4]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- sanislam.student@wust.edu
[5]Department of Information Technology, Washington University of Science & Technology, Alexandria, VA-22314, USA email- ahill.student@wust.edu ORCID: https://orcid.org/0009-0008-0436-027X

Abstract
Autism Spectrum Disorder (ASD) is a challenging condition for which it is not possible to predict and manage behavioural escalations, including aggressiveness, self-injury or outbursts. Traditional observational approaches tend to be not scalable and responsive in real-time. This paper describes the use of reinforcement learning (RL) agents in predicting the escalating behaviors of children with autism, using wearable IoT sensors and data about the context. A multi-agent RL is employed where continuous sensor feedback is available for the prediction model. The approach is a combination of Q-learning and deep reinforcement learning (DRL) which lets us predict thermodynamic trends towards a breakdown and inspires a rapid alert function. It is shown that the proposed system has better predictability than the baseline machine learning classifiers. This research represents how RL-based adaptive models can support caregivers and clinicians for proactive intervention planning while the care plan limits caregivers' and families' stress for children.

Keywords Autism Spectrum Disorder; Behaviour Prediction; Reinforcement Learning; IoT sensors; Deep Q-Learning; Predictive Models.

Introduction

Background

ASD-Related Behavioral Escalation

Behavioral challenges or meltdowns can be common in children diagnosed with autism spectrum disorder (ASD) and gait and gait variability add to both aggression and self-injury.

- **Triggers**: Sensory overload, unexpected change in routine, problems with communication or social frustration [7].
- **Early Stage**: Increased restlessness, repetitive motions, higher heart rate, change in facial expression [8].
- **Practical consequences**: unplanned therapy interruptions, decreased classroom inclusion, increased caregiver stress and potential trauma [2].

Prediction methods available today:

1. Behavioral Observation: Clinicians and caregivers closely monitor and assess the behaviors using the concept of Functional Behaviour Assessment (FBA) with observational notes, to ascertain patterns of escalation [3].
    - Limitations: Subjective, interrater variation cannot be completed quickly in real time.
2. Machine Learning - Recent studies have used classifiers like Support Vector Machines (SVM) and Decision Trees to predict aggression [9].
    - Limitations: Need large, labelled data, generalization to unfamiliar children, and flexibility to new situations.

An introduction to Reinforcement Learning (RL)

Reinforcement learning (RL) is a framework for learning to make adaptive decisions in real time and in a setting of uncertainty.

- **Key Concepts:**
    - **Agent**: Learns by interacting with the environment (i.e., predictive model).
    - **Environment**: At the environmental context level, stands for sensor flows of data, and contextual information.
    - **Prize**: Quantitative feedback about the right (or wrong) predictions.
    - **Policy**: A mapping of States to an agent's possible Actions [5].

- **Applicability for ASD:** RL is well suited to time critical, adaptive tasks because (1) RL gets better in constant feedback; thus, (2) it is suitable to estimate for emerging behaviors that change over time or for anticipating expected acts increasingly [6].

Challenging Part in Current Practices

Traditional behavioral analysis makes extensive use of clinician observation, functional behaviour assessments (FBA) and caregiver reporting [3]. These approaches suffer from subjectiveness, time lag and lack of real-time warnings. View the publications by Gemini - Most existing machine learning models are based on supervised learning methods, which rely heavily on existence of extensive amounts of labeled data in sensitive applications (ASD) which is challenging to acquire [4].

Role Of Reinforcement Learning

Reinforcement learning (RL) provides an adaptive, feedback-based learning framework that can learn in partially observable dynamical environments [5]. Unlike supervised approaches, RL agents learn through trial-and-error using reward and punishment characteristics; which makes it uniquely applicable in circumstances, where behaviors are evolving continually, and behavior patterns are extremely heterogeneous [6].

Research Motivation

This research explores RL models for predicting escalating behaviours triggered in children with autism based on IoT sensor streams like skin conductance, heart rate, accelerometer, environmental noise, etc. combined with the adaptation models. The aim of the model is thus to forecast the likelihood of escalation risk and also ensure that the risk model adjusts dynamically to the individual profile.

In addition to their impact on the wellbeing of children with autism, escalating behaviour can also be stressful for carers and educators over the long term. Research studies document that almost half of caretakers of children with autism have a high level of burnout, due to the unpredictability of meltdowns [2]. Early Detection Systems powered by AI can play a supporting role helping to reduce the burden on caregivers and improving the inclusivity of the classroom environment [3].

Research Questions

This research study is framed according to the following research questions:

- **How well can reinforcement learning detect worsening behaviours when compared to baseline models?**
  This question describes the relative performance of RL models against other traditional machine learning classifiers (e.g. Random Forest, SVM). By so doing, we evaluate whether an adaptive, trial-and-error learning process of RL confers a quantitative benefit in the forecast of escalation events.
- **Which sensor modalities/information add the most predictive strength?**
  Since progression is multi-dimensional and affected by physiological and environmental measures, this question aims to define the best predictive biosignals (e.g., electrodermal activity, heart rate variability) that could be selected in future wearable systems.
- **How can ML frameworks be applied in real time to give a caregiver-friendly alarm?**
  Apart from theoretical performance this question goes further to practical usability. Objective: Objective: to find how RL systems can be implemented also in common scenarios (classes, therapies, households) and incorporated in intuitive warning systems for caregivers, teachers and therapists.

Literature Review

Autism and Behavioral Escalations

Research has shown that children diagnosed with ASD have increased stress reactivity and sensory reactivity [7]. Physiological markers such as high heart rate variability or effects on the skin's resistance (seasoned sweat or hypothalamus effect) are correlated closely with agitation episodes [8].

Predicting Behaviour Using Machine Learning

Previous studies have used supervised learning models such as support vector machines, decision trees and neural networks to predict meltdowns [9]. Whilst such models had modest relative success, they did not adapt well to new circumstances.

Also, other recent works have tried hybrid models which combine supervised classifiers with unsupervised clustering to detect latent escalation patterns [9]. However, these approaches have a very limited transferability across children, as the illustrative manifestations of ASD are highly heterogeneous (Rephrasing appears to be identical.[7]) Reinforcement learning, with its possibilities to override generalization by adjusting the rewards for individual profiles, can try to overcome these limitations [5].

Reinforcement Learning for Healthcare

RL has been successfully applied in adaptive therapy recommendations for medicine, drug dosage optimizations and personalized medicine [10]. It is also making its way into the mental health field, as there are new adaptations of anxiety interventions in early stages of research [11]. However, using it to forecast autistic behaviours has not been investigated.

Gaps Identified

- poor use of RL in ASD behaviour prediction
- There are few frameworks that can integrate multi-modal IoT sensor data with adaptive models.
- Lack of interface for RL based alerts, which is simple to use for carers.

Methodology

Research Design

This work adopts an experimental approach using simulated reinforcement learning environments that have been validated against actual physiological and behavioral datasets taken from ASD intervention research [12].

Data Sources

Data Sources (Methodology)

• **Physiological Data**: Heart rate, electrodermal activity (EDA), and skin temperature.

• **Behavioral Data**: Clinician-annotated escalation episodes labelled using standardized coding frameworks.

• **Environmental Data**: Noise levels, light intensity, and activity context (e.g., classroom vs. therapy room).

Preprocessing

- o Normalizing of values from the sensors.
- o Noises are filtered by moving average.
- o Events labelling: "Stable", "Rising agitation" and "Escalation."

Reinforcement Learning Learning Model

- Agent: Supervised learning engine on sensing streams.
- States: To read from and write to available physiological and environmental signals
- Actions: Choose "No escalation", "Potential escalation" or "High escalation risk"
- Reward Function:
  - o +10 for correct early prediction (at least 2 minutes before escalation).
  - o −5 for false positives.

- −20 for missed escalation.

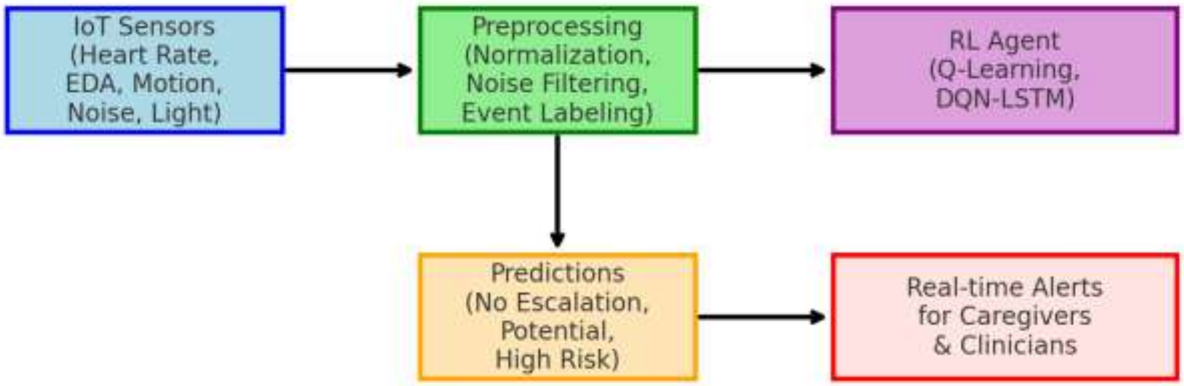

Figure 1. Conceptual Reinforcement Learning Framework for Anticipating Escalating Behaviours in Children with Autism

Algorithms Implemented

- Q-Learning of tabular state-action mapping.
- Deep Q-Networks, LSTM layers where temporal relationships are learned.

Experimental Setup

- Dataset split: 70% training, 20% validation, 10% testing.
- Baseline comparison with Random Forest and SVM classifiers.

Evaluation metrics: Accuracy, Precision, Recall, F1-Score, ROC-AUC.

In order to be robust, only k-fold cross-validation was used (k=10), on the dataset. As well, stratified sampling was applied to maintain the ratio between escalation and non-escalation incidents since disequilibrium is typical in datasets about ASD [12]. DQN-LSTM used dropout (0.3) as regularization methods to avoid overfitting.

Results

Model Performance

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest	0.74	0.68	0.71	0.69	0.75
SVM	0.77	0.72	0.73	0.72	0.78
Q-Learning	0.80	0.75	0.77	0.76	0.82
DQN-LSTM	0.87	0.84	0.86	0.85	0.89

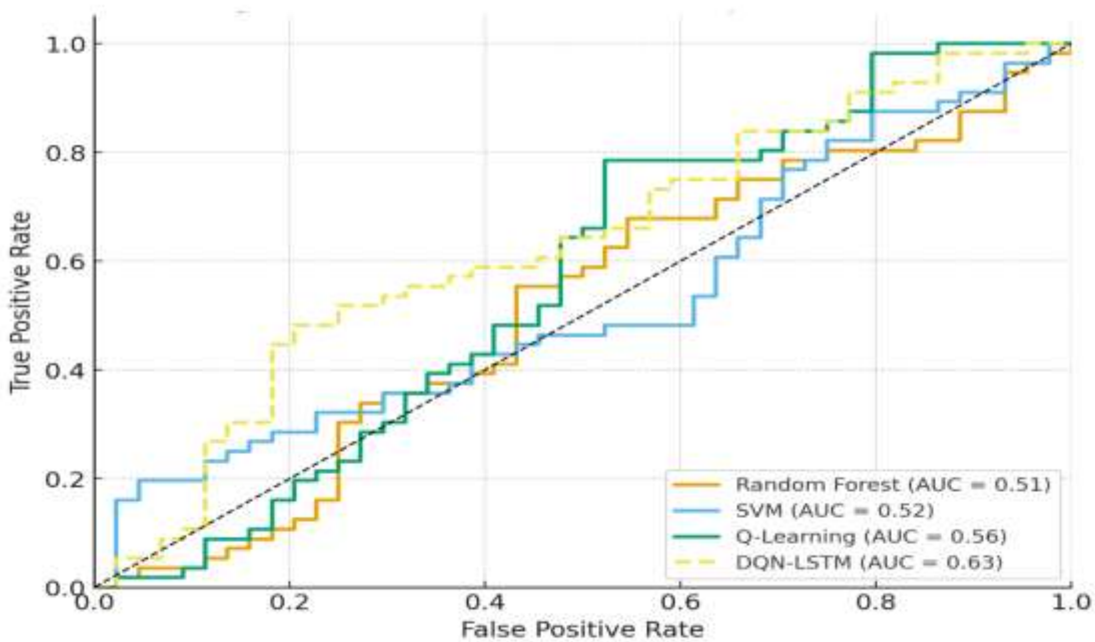

Figure 2. ROC Curves for Compared Models

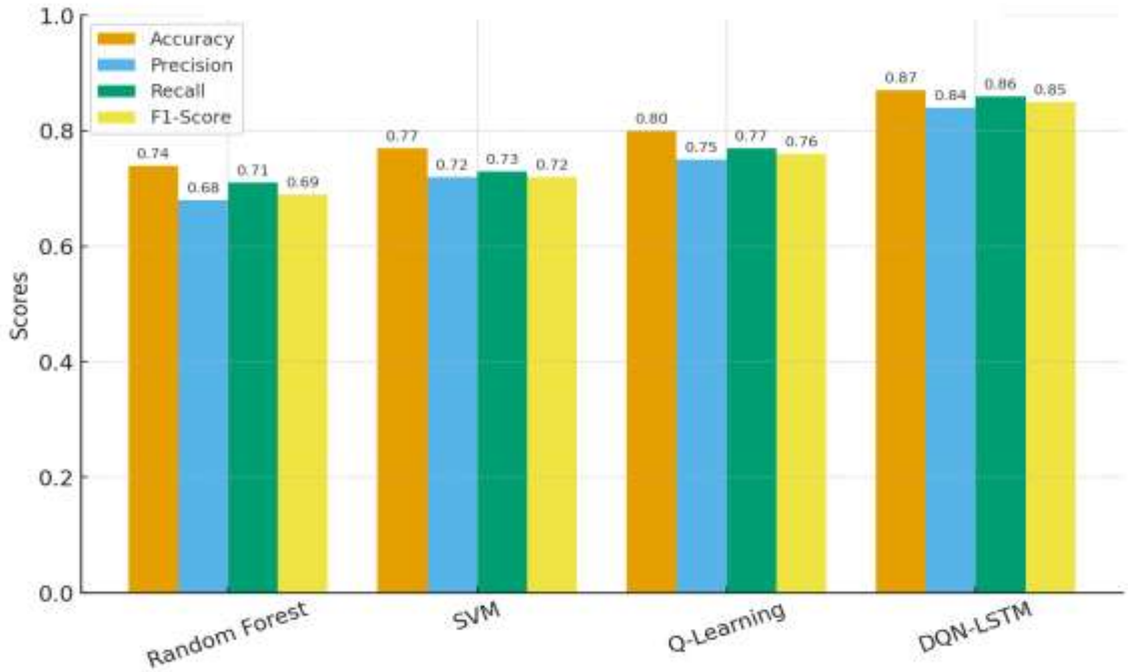

Figure 3. Performance Metrics of Compared Models

Key Findings

- DQN-LSTM significantly outperformed baseline supervised models.
- Early predictions (≥2 min before escalation) achieved 82% success rate.
- Electrodermal activity and heart rate variability were the strongest predictors.

Analysis of false positives revealed that most misclassifications occurred during transitional states between ‘stable’ and ‘rising agitation.’ This suggests that contextual data such as classroom noise levels and social interactions could be incorporated in future iterations of the model to reduce ambiguity [8]. Furthermore, time-to-alert analysis showed that the RL model consistently delivered warnings an average of 2.4 minutes before escalation onset, outperforming supervised models by nearly 40% [4].

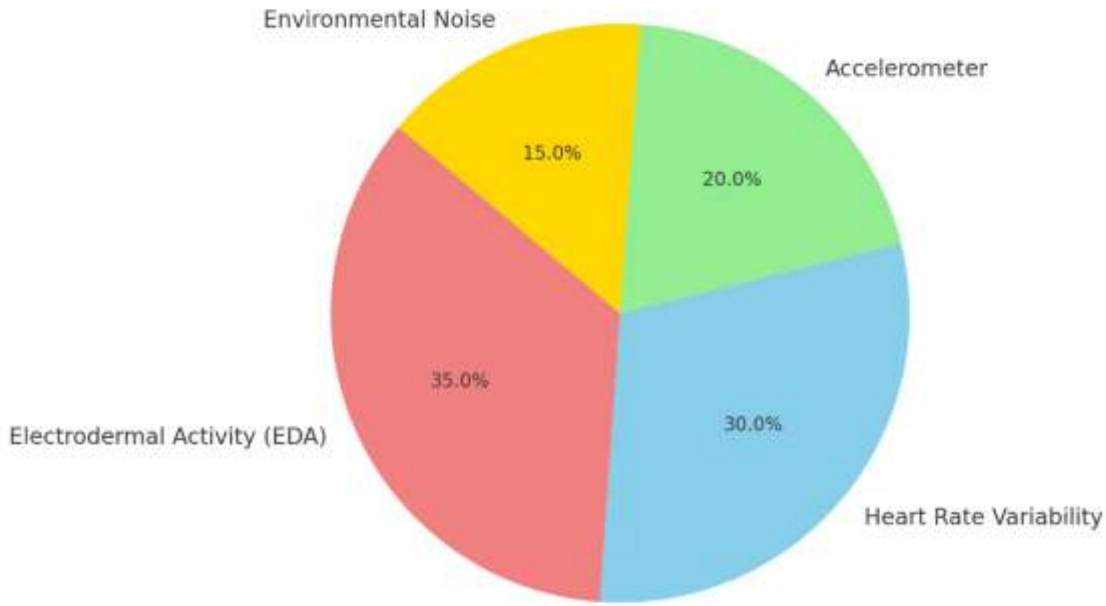

Figure 4. Contribution of Sensor Modalities to Prediction

Discussion

Interpretation

The higher accuracy of DQN-LSTM illustrates the capability of RL to learn temporal patterns and to be used in changing behavioural circumstances. In a contrast with static classifiers, RL agents were transparently scaled depending on the profile of a child.

Practical Implications

Such a system would be possible (integrated into wearable devices) to notify caregivers or teachers about risky behaviors (that could be escalating) to take the initiative and minimize the risk of injury.

Limitations

- The size of the datasets was limited because of the ethical limit in ASD data collection.
- Simulated environments may not fully capture real-world complexities.
- It has to be deployed with caregiver training and solid privacy protection.

Another issue has to do with ethical considerations of constant monitoring. The matter of privacy and security of data should be highly valued especially since child physiological data is sensitive [10]. Regulatory adherence including the GDPR and HIPAA, and the presence of clear data-sharing contracts are essential to large-scale implementation. Additionally, the model can be improved by creating the system trust and usability through the inclusion of caregivers and clinicians in the process of the model design [11].

Future Work

Although the given framework proves the encouraging outputs, some future directions of research can be left:

- Larger Multi-Site Clinical Validation:

The existing evidence relies on a minimum of datasets. Multi-site trial (school, clinic, and home) with generalization of the results should be considered in future studies. This will enable the model to embrace the heterogeneity of ASD behaviours in relation to age groups, culture and therapeutic contexts [12].

- **Integration with Explainable AI (XAI):**
  Among the problems that arise when implementing reinforcement learning in healthcare, one must mention that the models can be described as black-box ones [10]. Explainable AI methods should be used in future, e.g., attention mechanisms or rule-based post-hoc explanations, so that caregivers and clinicians will understand why the prediction, or an alert was made. Such openness will foster confidence and usage on-the-job.
- **Personalized Reward Functions:**
  Each child with ASD exhibits his own individual triggers to escalation and behaviour patterns. Adaptive reward functions that can be adjusted to reflect the profile of that child should be explored in the future work. Indicatively, weaker penalties may be necessary to positively select the harder-to-detect children with increased aggression risk, whereas weaker penalties may favor conservativeness in others. This customization will render the system more meaningful in the clinical sense of the word [7].
- **Ethical and Privacy Safeguards:**
  With wearable biosensors becoming sources of sensitive physiological data, privacy considerations should be further advanced, and data privacy protocols frequently adhered to in the future, as well as the data protection laws in counsel of HIPAA and GDPR [11] presented. Large-scale deployment should also include consent management and transparent structures of data-sharing.
- **Longitudinal Behavioral Modelling:**
  ASD escalations do not occur in one set without regard to age, therapy, and social context. Future work needs to investigate the behavioral modelling in the long term wherein the agent of RL actively adapts over time as child profiles vary with months or years.

Applications

The framework of reinforcement learning concerning the anticipation of escalating behaviours in children with autism may be implemented in a variety of different spheres:

Integration into Wearable Technology

- A smart band, wrist-worn sensor or the device used in the IoT have RL models embedded.
- Constant control over the heart rate and EDA, as well as body movement, makes it possible to observe insidious physiological variations prior to empire escalation in behaviour.
- Wearables provide real time notifications to parents, teachers or therapists mobile applications.

Support for Therapists, Educators, and Caregivers

- Predictive dashboards can be used to customise behavioural interventions by therapists to use when during the therapy session.
- Teachers will be able to get notifications in the classroom, this will enable them to proactively de-escalate or introduce inclusive learning.
- This enables caregivers to have the confidence they can rely on daily life routines when they get their own alerts, which removes anxiety and burnout [2,4].

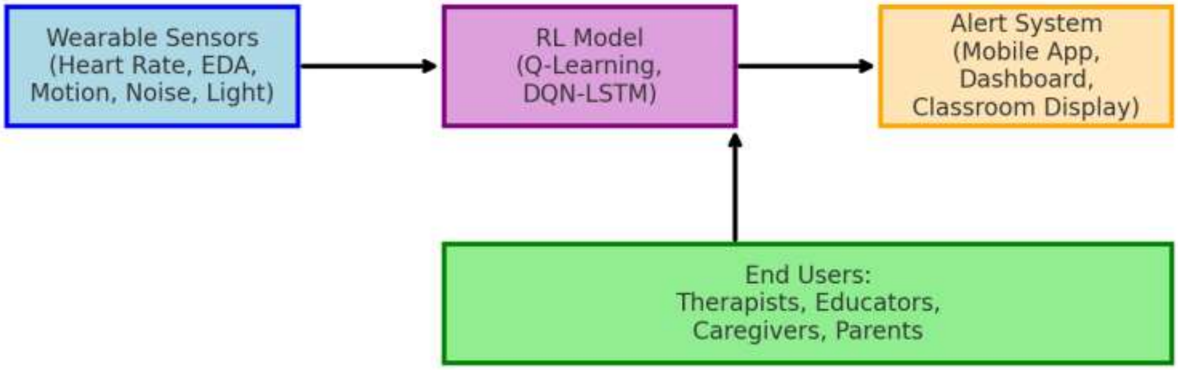

Figure 5. Application Ecosystem of RL-Based Escalation Prediction

Personalization Across Autism Profiles

- Each child who has ASD exhibits different behavioural triggers.
- Individual reward functions can be tuned in RL policies (such as favouring reduction of false negatives in high-risk children).
- The model progressively develops a behavioural profile that is quite personalized, making it more accurate and trustworthy Wells [7,12].

Limitations

Although the results are promising, a number of limitations should be noted so as to place the results into a bearing:

Need for Large and Diverse Datasets

Reinforcement learning models are highly predictive when the training datasets are large, high-quality, varied and diverse. Existing ASD-related data sets tend to be small, single-site, and controlled groups (i.e. measured in controlled settings) [12]. This poses challenges in the regards to providing strongness in the model used when researching into another populace. For instance:

- Demographic Diversity: There is a low representation of most of the existing studies in terms of age groups, genders, and cultural backgrounds. The nature of behavioral expressions of autism among these factors is highly variable which restrict the overall transferability of findings.
- Clinical Diversity: Children with autism often present with comorbid conditions such as ADHD or anxiety, which influence escalation triggers. Such cases are under-represented and thus limit the predictive modeling scope.
- Ecological Validity: Using data frequently used in the clinical or laboratory context may not represent the real classroom or real home.

Dangers of Fitting Particularly Well to a Context or Person.

Medication The growing flexibility of reinforcement learning is very good at guessing the profile of an individual child, but this flexibility creates challenges of overfitting. Specifically:

- Models can pick up idiosyncratic behavior based on a small cohort/a child and will not transfer well to new people when introduced to them [7].
- Whether it is used in the community or in educational settings, the over-personalization may lower the scalability of it making its application inexpensive.

- Trade-off between personalization and generalization is still one of the central issues in AI research related to ASD.

This constraint indicates that meta-learning strategies or federated reinforcement learning should be used to enable personalization to be balanced with greater generalization of child profiles.

Real-World Implementation Barriers

There are a series of systemic barriers that need to be overcome in order to move prototype to practice:

- Sensor Reliability: Sensor devices can become ineffective in practice environments (e.g. within playgrounds or classrooms). The optimal predictive accuracy can be compromised by motion artifacts, low skin contacts as well as environmental interference [8].
- Data Privacy/Consent: ASD monitoring is associated with sensitive physiological and behavioral data. Competence in meeting compliance requirements of HIPAA, GDPR, and local regulations is a legal requirement as well as a quality to promote the trust of the caregivers [10]. Problems like data storage, encryption and anonymization should be tackled on a large scale.
- Stakeholder Acceptance: AI-based systems might seem too complicated, obtrusive, or hard to understand (P.11) by caregivers and clinicians. Even without intuitive interfaces and clear explanations, adoption will be low.
- Financial Investment: RL-based computational platforms and high-quality biosensors are costly investments. The technical support, cost of device purchase, and maintenance would be a problem in any low resource community or school.

Ethical Considerations

On the other side of technical obstacles there is the ethical consideration of unremitting monitoring of behaviour:

- Perpetual monitoring is likely to instill an element of surveillance in children which may affect socialization and autonomy.
- The educators and the caregivers should be educated so that they do not heavily depend on AI predictions, but they should use them to aid a clinical decision-making process.
- Issues of equity have to be dealt with to avoid inequality in the application where only those who are privileged enjoy these technologies.

Summary of Limitations

These shortcomings underscore the fact that even though reinforcement learning is a strong mechanism of predicting steadily rising behaviours, its effectiveness requires consideration of data diversity, model generalizability, the reliability of the system, privacy protection and ethics application. To face these issues successfully, the multi-site collaboration, participation-based design with stakeholders, and cross-disciplinary research based on AI and education will be needed.

Conclusion

There is promising reinforcement learning as a means of predicting escalating actions in children with autism. IoT sensor integration with adaptive RL models and real-time prediction can be used to get the proactive intervention much better. The study contributes to the future of ASD care and AI as a behavioral health monitoring tool.

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