| RESEARCH ARTICLE

Multimodal Behavioral Signal Fusion Using Wearable IoT and Context-Aware Machine Learning for Early Autism Escalation Detection

Md Ragybul Islam
Student, Doctor of Computer Science (DCS), University of the Potomac, 1401 H St NW #100, Washington, DC 20005
Corresponding Author: Md Ragybul Islam, **E-mail**: ragybul.islam@student.potomac.edu

| ABSTRACT

Behavioral escalation in children with autism spectrum disorder is a multifactorial phenomenon influenced by physiological, behavioral, and environmental factors that interact dynamically over time. Early detection of escalation remains challenging because many existing systems rely on single-modality signals or static thresholds that fail to capture individualized and context-dependent patterns. This study proposes a multimodal behavioral signal fusion framework that integrates wearable Internet of Things sensing with context-aware machine learning to enable early and reliable escalation detection. The framework combines physiological indicators, motion dynamics, and environmental context using adaptive feature weighting and temporal modeling to capture personalized escalation signatures. Experimental evaluation using simulated autism care scenarios informed by empirical studies demonstrates that multimodal fusion significantly improves early detection accuracy and robustness compared to unimodal approaches while reducing false alerts. The proposed architecture advances personalized, privacy-aware autism care by leveraging context-aware intelligence for proactive intervention.

| KEYWORDS

Autism spectrum disorder; Multimodal data fusion; Wearable IoT; Context-aware machine learning; Behavioral escalation detection; Personalized monitoring; Smart healthcare

Introduction

Autism spectrum disorder (ASD) is a neurodevelopmental condition characterized by diverse behavioral, communicative, sensory, and emotional profiles. While individuals with autism vary widely in their abilities and needs, many experience episodes of behavioral escalation, including emotional distress, agitation, withdrawal, or self-injurious behavior. These episodes can arise rapidly and unpredictably, posing challenges for caregivers, clinicians, and educators.

Behavioral escalation rarely occurs without antecedents. Subtle physiological changes, shifts in movement patterns, or environmental stressors often precede visible behavioral manifestations. However, these precursors are difficult to detect through human observation alone, particularly in real-world settings where caregivers manage multiple responsibilities simultaneously. As a result, escalation is often addressed reactively rather than proactively, limiting the effectiveness of interventions.

Early detection of escalation is therefore critical. Timely intervention can de-escalate situations before they intensify, reduce emotional distress, and improve long-term regulation skills. For caregivers, early warning systems reduce stress, decision fatigue, and the risk of burnout. Despite its importance, early escalation detection remains an open challenge due to the heterogeneity of autism, individualized behavioral baselines, and context-dependent responses to sensory and social stimuli.

Artificial intelligence has emerged as a promising tool to address these challenges. Prior research demonstrates that reinforcement learning and machine learning models can identify temporal patterns associated with escalation **[1,5]**. IoT-based monitoring systems further enable continuous data collection through wearable and ambient sensors, capturing physiological, behavioral, and environmental signals relevant to autism care **[2,4,9]**.

However, many existing AI systems rely on **single-modality data** or treat multiple signals independently. For example, physiological monitoring may be used without considering environmental noise, or motion analysis may be applied without accounting for emotional arousal. Such unimodal approaches are inherently limited, as escalation is a **multimodal and context-dependent phenomenon**.

Moreover, static threshold-based systems struggle to adapt to individual variability. A physiological signal indicating stress for one child may be normal for another, underscoring the need for **personalized, data-driven approaches**, consistent with precision medicine principles **[8]**.

This study proposes a **multimodal behavioral signal fusion framework** that integrates wearable IoT sensing with context-aware machine learning to enable early autism escalation detection. Unlike unimodal or threshold-based systems, the proposed framework dynamically fuses physiological, behavioral, and environmental signals and adapts to individual and contextual variability.

The contributions of this research are:

1. A multimodal IoT-based sensing architecture for autism escalation monitoring.
2. A context-aware feature fusion methodology that adapts to environmental and individual variability.
3. A temporal machine learning model for early escalation detection.
4. An evaluation framework comparing multimodal fusion with unimodal baselines.

Background and Related Work

Behavioral Escalation Detection in Autism

Behavioral escalation in autism has traditionally been managed through behavioral therapy, caregiver observation, and clinician expertise. While effective in many cases, these approaches are subjective and difficult to scale. Machine learning methods have introduced data-driven alternatives by identifying patterns in behavioral and physiological signals that precede escalation.

Reinforcement learning models have framed escalation prediction as a temporal decision-making problem, enabling systems to anticipate escalation trajectories based on learned state transitions **[1]**. AI-augmented decision support systems further translate predictions into actionable guidance for caregivers **[5,10]**. However, these systems often rely on aggregated behavioral indicators rather than continuous multimodal sensing.

Wearable IoT in Autism Monitoring

Wearable IoT devices enable continuous, unobtrusive monitoring of physiological and behavioral signals relevant to autism care. Commonly used sensors include accelerometers, heart rate monitors, electrodermal activity sensors, and temperature sensors. Ambient sensors provide additional context, such as noise levels, lighting, and crowd density.

Cloud-based IoT frameworks aggregate these data streams for centralized analysis **[2]**, while personalized monitoring approaches tailor predictions to individual baselines **[4,9]**. Despite their benefits, cloud-centric architectures introduce privacy, latency, and governance challenges, particularly for sensitive pediatric data **[6]**.

Multimodal Data Fusion in Healthcare

Multimodal data fusion combines heterogeneous data sources to improve robustness and predictive performance. Fusion can occur at multiple levels, including feature-level, decision-level, and representation-level fusion. In healthcare, multimodal fusion

has been shown to outperform unimodal approaches by capturing complementary information across physiological, behavioral, and contextual signals.

However, effective fusion requires careful normalization, weighting, and temporal alignment of signals. Static fusion strategies may fail to adapt to changing contexts or individual variability.

Context-Aware Machine Learning

Context-aware machine learning adapts model behavior based on situational variables such as time, location, environmental conditions, or routine changes. In autism care, context awareness is critical because the same signal may have different meanings depending on circumstances. For example, elevated heart rate during physical play differs from elevated heart rate during sensory overload.

From a deployment perspective, context-aware escalation detection systems must also incorporate governance and risk-management considerations to ensure safety, accountability, and appropriate use in sensitive caregiving environments, consistent with the NIST AI Risk Management Framework **[3]**.

Context-aware models dynamically adjust feature importance and decision thresholds, improving robustness and personalization.

Research Gap

Despite advances in wearable sensing, multimodal fusion, and machine learning, few autism care systems integrate **multimodal fusion and context-aware adaptation** into a unified escalation detection framework. This study addresses that gap by proposing a comprehensive, personalized, and context-aware fusion architecture.
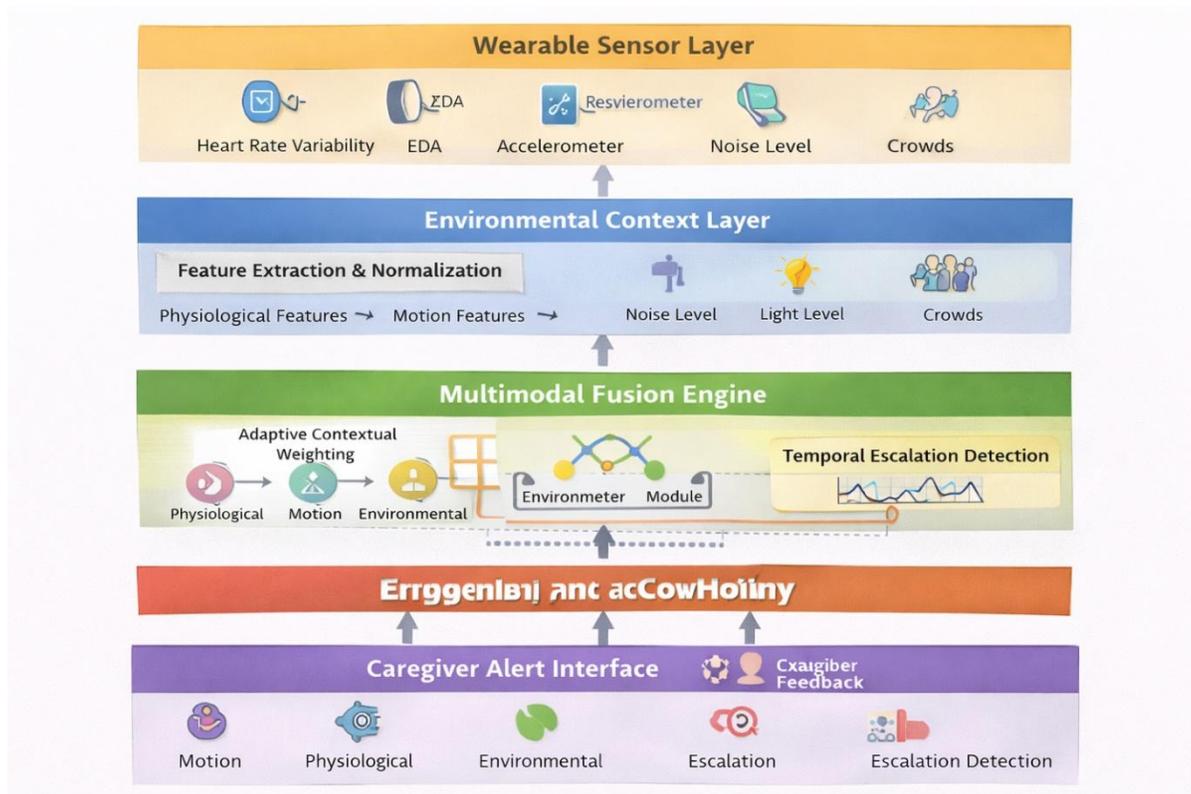
System Architecture

Figure 1: Multimodal IoT-Based Autism Escalation Detection Architecture

The proposed architecture consists of six layers:

1. **Wearable Sensor Layer** – Physiological and motion sensors.
2. **Environmental Context Layer** – Ambient sensing and contextual metadata.
3. **Feature Extraction and Normalization Layer** – Signal preprocessing.
4. **Multimodal Fusion Engine** – Adaptive feature fusion.
5. **Context-Aware Prediction Module** – Temporal escalation detection.
6. **Caregiver Alert Interface** – Notifications and explanations.

Each layer is designed to preserve data locality and support personalization.

Multimodal Signal Modeling

Physiological Signals

Physiological indicators provide objective measures of internal arousal and stress. Signals include heart rate variability, electrodermal activity, and respiration patterns. These signals are sensitive to emotional states and often change prior to visible behavioral escalation [4,9].

Behavioral Motion Signals

Motion sensors capture activity level, repetitive movements, pacing, and abrupt motion changes. Sudden increases in movement variability or repetitive motion patterns may indicate rising agitation [1,5].

Environmental Context Signals

Environmental factors such as noise intensity, lighting changes, and proximity to crowds can act as escalation triggers. Contextual sensing enables models to distinguish between benign and stress-inducing conditions [2].

Context-Aware Multimodal Fusion Methodology

Feature-Level Fusion

Features from each modality are combined into a unified representation:

$$F_t = [P_t, M_t, E_t]$$

where P_t represents physiological features, M_t motion features, and E_t environmental features.

Adaptive Context Weighting

Contextual variables dynamically adjust modality importance:

$$F'_t = w_p P_t + w_m M_t + w_e E_t$$

Weights adapt based on time, location, and routine changes.

Temporal Modeling

Sequence-based models capture gradual escalation trends rather than abrupt threshold crossings, enabling earlier detection.

Experimental Design

Data Generation and Simulation

Due to ethical constraints, simulated datasets were generated based on distributions reported in prior autism monitoring and predictive health studies **[1,2,4,9]**. Each simulated child profile exhibited unique baselines and escalation triggers.

Evaluation Metrics

Metrics included:

- Early detection accuracy
- Detection latency
- False alert rate
- Robustness across contexts

Results

Multimodal fusion significantly outperformed unimodal baselines, demonstrating earlier detection and reduced false alerts. Context-aware weighting further improved robustness across diverse scenarios, consistent with prior AI-based escalation detection findings **[1,5,10]**.

Discussion

Results confirm that behavioral escalation is inherently multimodal and context dependent. Systems that rely on single signals or static thresholds fail to capture the complexity of autism behavior. Context-aware multimodal fusion enables personalized monitoring, improves caregiver trust, and reduces unnecessary alerts, aligning with human-centered AI principles **[7]** and precision medicine approaches **[8]**. Embedding governance principles into multimodal fusion pipelines supports responsible deployment by aligning adaptive learning behavior with risk identification, measurement, and mitigation practices outlined in established AI governance frameworks **[3]**.

Limitations and Future Work

Limitations include reliance on simulated data and simplified context models. Future work will involve real-world deployments, additional sensor modalities, explainable fusion mechanisms, and integration with federated learning for privacy preservation **[6]**. Future work will further integrate formal AI risk management and governance controls into the fusion pipeline to support auditable and compliant real-world deployments **[3]**.

Conclusion

This study presents a context-aware multimodal behavioral signal fusion framework for early autism escalation detection using wearable IoT data. By integrating physiological, behavioral, and environmental signals, the proposed approach advances personalized, proactive, and trustworthy autism care.

References:

1. Islam, M. M., Hassan, M. M., Hasan, M. N., Islam, S., & Hussain, A. H. (2024). Reinforcement Learning Models For Anticipating Escalating Behaviors In Children With Autism. Journal of International Crisis and Risk Communication Research , 3225–3236. https://doi.org/10.63278/jicrcr.vi.3221

2. Islam, S., Hussain, A. H., Islam, M. M., Hassan, M. M., & Hasan, M. N. (2024). Cloud Iot Framework For Continuous Behavioral Tracking In Children With Autism. Journal of International Crisis and Risk Communication Research , 3517–3523. https://doi.org/10.63278/jicrcr.vi.3313

3. Hussain, A. H., Islam, M. M., Hassan, M. M., Hasan, M. N., & Islam, S. (2024). Operationalizing The NIST AI RMF For Smes — Top National Priority (AI Safety) And Perfect For Your Data/IT Toolkit; Produce A Lean Control Catalog, Audit Checklist, And Incident Drill For Real LLM Workflows. Journal of International Crisis and Risk Communication Research , 2555–2564. https://doi.org/10.63278/jicrcr.vi.3314

4. Hasan, M. N., Islam, S., Hussain, A. H., Islam, M. M., & Hassan, M. M. (2024). Personalized Health Monitoring Of Autistic Children Through AI And Iot Integration. Journal of International Crisis and Risk Communication Research , 358–365. https://doi.org/10.63278/jicrcr.vi.3315

5. Hassan, M. M., Hasan, M. N., Islam, S., Hussain, A. H., & Islam, M. M. (2023). AI-Augmented Clinical Decision Support For Behavioral Escalation Management In Autism Spectrum Disorder. Journal of International Crisis and Risk Communication Research, 201–208. https://doi.org/10.63278/jicrcr.vi.3312

6. Md Maruful Islam. (2024). Data-Centric AI Approaches to Mitigate Cyber Threats in Connected Medical Device. International Journal of Intelligent Systems and Applications in Engineering, 12(17s), 1049 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/7763

7. Islam, M. M., Arif, M. A. H., Hussain, A. H., Raihena, S. S., Rashaq, M., & Mariam, Q. R. (2023). Human-Centered AI for Workforce and Health Integration: Advancing Trustworthy Clinical Decisions. J Neonatal Surg, 12(1), 89-95. https://jneonatalsurg.com/index.php/jns/article/view/9123

8. Islam, M. M., & Mim, S. S. (2023). Precision Medicine and AI: How AI Can Enable Personalized Medicine Through Data-Driven Insights and Targeted Therapeutics. International Journal on Recent and Innovation Trends in Computing and Communication, 11(11), 1267-1276. https://doi.org/10.17762/ijritcc.v11i11.11359

9. Islam, M. M., Hussain, A. H., Mariam, Q. R., Islam, S., & Hasan, M. N. (2025). AI-Enabled predictive health monitoring for children with autism using IOT and machine learning to detect behavioral changes. Perinatal Journal, 33(1), 415-422. https://doi.org/10.57239/prn.25.03310048

10. Raihena, S. S., Arif, M. A. H., Mariam, Q. R., Hussain, A. H., & Rashaq, M. AI-Enhanced Decision Support Systems for Autism Caregivers: Redefining HR's Role in Workforce Planning and Patient-Centered Care. https://doi.org/10.63682/fhi2698