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Approaches for Meltdown Detection in Children with Autism: A scoping review

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Abstract

Purpose - The purpose of this paper is to review studies relevant to the early identification of behavioural changes in children with autism when they start to feel overwhelmed and use their detection for the timely launch of evidence-based well-being interventions for their mitigation.
Design/Methodology/Approach - A scoping review of electronic databases was undertaken focusing on the studies related to emotions or arousal detection in children with Autism.
Findings - The literature selected for this research explores different methodologies used for detecting precursors of emotional dysregulation (termed meltdown) in individuals with autism. Results suggest that use of multi-modal data is an under researched area, further compounded by the lack of accessible state of the art data sets.
Originality/value - This paper is first of its type aiming to review and categorise existing literature related to approaches for emotion and arousal detection in children with Autism to identify gaps where contemporary computer science methods may help.

Keywords: Autism, ASC, Rumble moments, Emotional dysregulation, Arousal, Tracking, Engagement, Behavioural data, Physiological signals, Wearables
Paper Type - Literature Review

1 Introduction

The Diagnostic and Statistical Manual of Mental Disorders, 5th Edition classified Autism Spectrum Condition (ASC) as a heterogeneous group of neurodevelopmental disorders. The prevalence rate of ASC is on the rise, where at least 1 in 100 children in the United Kingdom and 1 in 68 children in the United States are diagnosed being on the autism spectrum (National Autistic Society 2018; Disease Control and Prevention 2020). It is a complex disorder in which people often show repetitive patterns of activities and interests (Friedrich et al. 2014), have stereotypical behaviours (White et al. 2009) and face challenges in interacting socially which can lead to issues such as isolation and anxiety. Consequently, anxiety is common in autistic people affecting their mental and emotional well-being (Kushki, Drumm, et al. 2013).

Due to deficits in communication, children with ASC are more likely to be affected by alexithymia i.e, they are unable to express their mental and emotional state and neither able to understand that of others (Sifneos 2010; Cheng et al. 2018) as compared to neurotypical children, thus creating a disconnect between their emotional arousal and conscious awareness (Sarabadani et al. 2020). This may often cause challenging or disruptive behaviours commonly termed 'meltdowns' or 'tantrums' in literature. The National Autistic Society (2020) defined meltdowns as a reaction to an overwhelming situation resulting in losing control over their emotions (O'Nions et al. 2018; Tarver et al. 2021). There could be several reasons for these distressing episodes such as sensory overload due to stimuli present in the environment, an unfulfilled need which may lead to an emotional overload or cognitive overload due to incapability of performing a desired task (Turabee et al. 2023). These intense behaviours can manifest in the form of scratching, hitting, biting, kicking, screaming, crying, and hitting the floor, and may cause harm to caregivers, fellow children, and themselves (Chu et al. 2018).

Since ASC is a spectrum, it exhibits very differently from child to child. However, there are some common precursors that children might show before a meltdown which includes repetitive non-functional movements known as Stereotypical Motor Movements (SMMs). During this stage, the involuntary cues of distress that autistic children exhibit are atypical, but also less injurious (Al-Rammah, Masmoudi, and Jarraya 2022). This transitional phase of becoming emotionally distressed has been termed the 'rumbling stage' or 'rumble moments' (Myles and Hubbard 2005). Since self-assessments and reports in children with autism are not reliable due to the inability to communicate properly and express their emotions (Kushki, Drumm, et al. 2013), it is important for carers to be able to recognise that a child is feeling distressed or frustrated (Taheri, D. Brown, and Sherkat 2020) as it can help them to take precautionary measures before any episode of emotional dysregulation. Much research has been carried out aiming to determine the cues that a child with ASC may manifest before reacting to an overwhelming situation. Koo et al. (2018) state that almost 72% of parents of children with autism were willing to track physiological signals and patterns of body movements which may help in pre-empting distressing moments and thus avoiding intense challenging behaviour. There are many possible ways of labelling the emotional states of children with autism such as monitoring their facial expressions, postures and movements, eye gaze and physiological signals (Sarabadani et al. 2020; Standen et al. 2021). The increasing prevalence of ASC has led researchers to use machine learning approaches over traditional statistical methods when developing approaches to predicting the onset of such events (Hyde et al. 2019).

Over the years, several review studies have been conducted on emotion recognition, meltdowns, and tantrum detection in individuals with ASC. Hyde et al. (2019), Landowska et al. (2022), and Banos et al. (2024) reviewed the literature related to machine learning approaches for emotion detection in ASC. Khare et al. (2024) provided a comprehensive review emotion recognition techniques in general, without a specific focus on autism, whereas Al-Saadi and Al-Thani (2023) concentrated solely on mobile applications designed for emotion recognition in autistic children. Briot et al. (2021) and Rashidan et al. (2021) conducted systematic reviews of literature related to impairments in the recognition of facial emotion expressions and technology-assisted emotion recognition in ASC, but their focus was primarily on image and video-based approaches and not physiological signals. Furthermore, the majority of these studies have primarily emphasised general emotion recognition rather than emotional dysregulation, meltdowns, and tantrums in children with autism. The present study aims to provide a comprehensive and integrative review of both machine learning and statistical approaches used for detecting emotional dysregulation in autistic children, incorporating a wider range of data modalities.

2 Detection through facial expressions

An emotion is comprised of three components: the subjective part which describes how we experience it, the physiological component, which depicts the internal state of our body and then an expressive element which is related to how we behave in response to it (J. T. Cacioppo, L. G. Tassinary, and G. G. Berntson 2007). Being able to know what the user is feeling i.e., behaviour and emotions, is a very powerful tool in human-computer interaction. According to Plutchik's Wheel of Emotions model (Fig.1, Plutchik 1980), every human emotion is a combination of several primary emotions, namely, ecstasy, admiration, terror, amazement, grief, loathing, rage and vigilance. The rest are compound emotions resulting from combinations of these primary emotions (Garcia-Garcia et al. 2019). Undoubtedly, facial expressions are some of the most raw and apparent displays of one's emotions and also the most common and immediate way to communicate them (Hassouneh, Mutawa, and Murugappan 2020).
Symptoms of meltdown in children with autism are largely associated with changes in their facial expressions exhibiting compound emotions such as fear, anger and sadness (Jarraya, Masmoudi, and Hammami 2021). Antecedent intervention, when a child starts to show any kind of atypical repetitive stereotyped actions or distressing behaviour, can have the most impact (A. Q. Alban et al. 2021). Using computer vision, we can collate these involuntary cues that a child exhibits before the onset of an emotional dysregulation event (Bonacini, Mahmud, and D. J. Brown 2023). Detecting emotions and movements of children with ASC involves emotion recognition and activity recognition. For this purpose, spatial and temporal components can be used from videos taken of children during these states. The spatial component will give appearance information from each frame while the temporal component captures movement information (Al-Rammah, Masmoudi, and Jarraya 2022). Thus, SMMs along with facial expressions can be monitored through a system which can alert the caretaker before more serious dysregulation occurs - with accompanying negative outcomes such as the child hurting themselves or causing classroom disruption.

3 Detection through physiological signals

As deduced from the Polyvagal theory (Porges 2009), every psychological reaction has a physiological basis to it. Physiological signals change according to our emotions and provide additional cues when interpreting affective states. Researchers have been using various behavioural measures such as facial expressions, gestures, and speech to understand the emotional states of people with special needs. However, these methods may not always represent the true internal state as they can easily be masked. Emotion elicitation based on the physiological signals of a person can be used to overcome these issues. Literature suggests that physiological arousal is an objective indicator of any emotional dysregulation that the child is going to face (Lindsay and Anderson 2000; Goodwin et al. 2018). Human body vital signals such as Heart Rate(HR), Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), etc can depict the internal state of a person. There is very little research on the identification of the internal state of children with ASC based on physiological signals (Legiša et al. 2013; Deschamps et al. 2015; Krupa et al. 2016; Di Palma et al. 2017; B. Anandhi et al. 2022). Management of physiological signals is an important part of dealing with meltdowns. However, due

Fig. 1: Plutchik's Wheel of Emotions model: A visual model created by psychologist Robert Plutchik that illustrates the relationships between eight primary emotions: joy, trust, fear, surprise, sadness, anticipation, anger, and disgust (Plutchik 1980)

to deficits in communication, children cannot self-recognise and self-analyse themselves and thus, have to be monitored in different ways.

Theoretically, anxiety lies around three interconnected dimensions which are: behavioural, subjective-cognitive and physiological. During an anxiety response, both the Central Nervous System (CNS) and Peripheral Nervous System (PNS) are involved. At the central level, the amygdala mobilises the body's fight or flight response while at the peripheral level, it arouses the Autonomic Nervous System (ANS). The ANS is a component of the PNS, responsible for involuntary control of the body such as cardiac activity, electrodermal activity, skin temperature, pupillary activity etc. (Kushki, Khan, et al. 2015). It is further divided into sympathetic and parasympathetic components. The sympathetic nervous system(SNS) prepares our body for stress-related activities while the parasympathetic nervous system(PNS) is associated with daily operations. Both systems work complementarily in tandem to maintain our body's state of equilibrium and this balance is reflected by the physiological signals of our body. Whenever an individual is experiencing emotional dysregulation, our body modulates physiological signals by elevating the sympathetic nervous system and suppressing the parasympathetic nervous system (Kreibig 2010). This results in increased electrodermal activity (Vetrugno et al. 2003), decreased fingertip temperature (Rimm-Kaufman and Kagan 1996), increased respiration rate (Kreibig 2010) and increased heart-rate (Franchini and Cowley Jr 2004).

R-R interval(interbeat interval) is the time between two heartbeats which is regulated by sympathetic and parasympathetic influences. The fight or flight in response to an emotional dysregulation event arouses the sympathetic branch of the ANS and suppresses the parasympathetic branch. This leads to a decrease in R–R intervals and an increase in the HR (*Heart Rate Variability — Circu-*

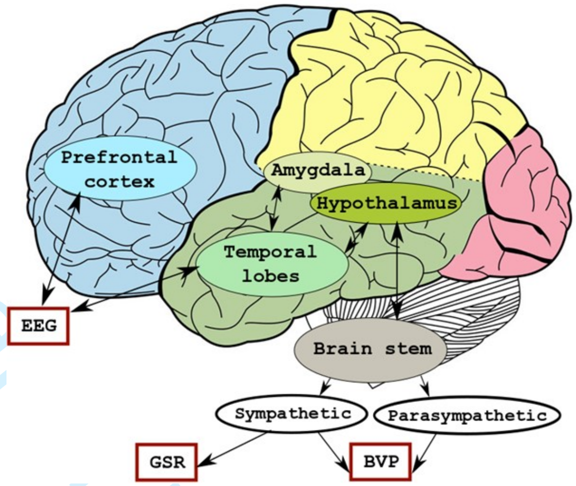

Fig. 2: Graphical depiction of the inter-relations between brain areas involved in emotion processing - ***partially modified*** (Val-Calvo et al. 2020)

lation 2023). Therefore, monitoring HR in children with ASC could give important information related to the onset of a distressing episode. The same goes for other sorts of physiological signals. Caregivers can make use of this information along with the behavioural cues for the prevention of any undesired event (Cheung et al. 2016).

4 Review Methodology

This literature search was conducted following the PRISMA extension for scoping reviews (PRISMA-ScR) (Tricco et al. 2018) and included the following steps:

1. Setting up research questions.
2. Defining the keywords for the search.
3. Deciding on the databases.
4. Defining inclusion and exclusion criteria.
5. Extracting studies from the search engines in multiple stages based on the criteria and research questions.
6. Extraction of key findings.

The focus of this study is on the role of AI approaches in detecting the onset of a meltdown event in children with autism. For this purpose, a scoping review was performed to systematically map the research carried out in this area, as well as to identify any existing gaps in knowledge. The key tasks achieved from this review are as follows:

– A review of studies conducted on different approaches used for pre-emptive determination of challenging behaviours in children with ASC.
– To analyse findings from the selected studies and identify any gaps in this research area.

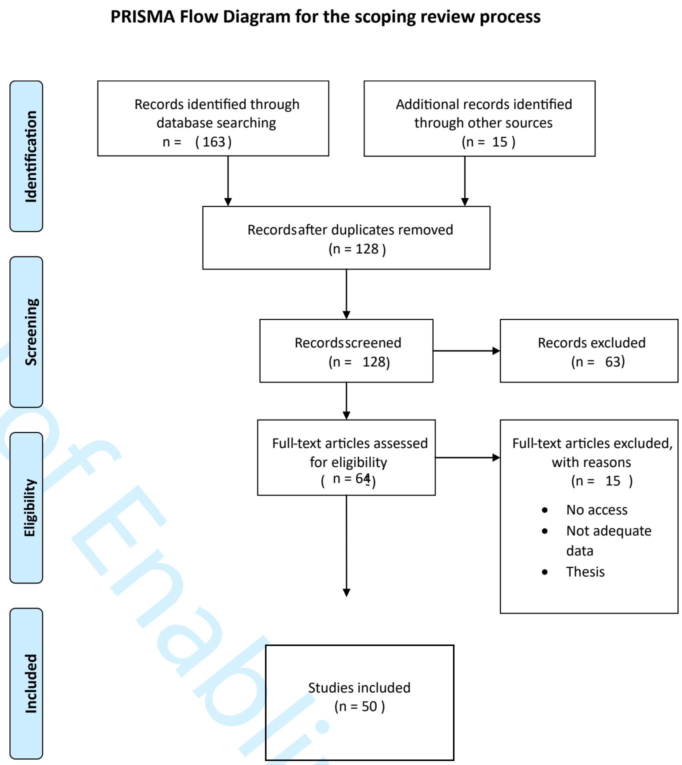

Fig. 3: PRISMA Flow Diagram (*Moher D, Liberati A, Tetzlaff J, Altman DG, The PRISMA Group (2009). Preferred Reporting Items for Systematic Reviews and Meta- Analyses: The PRISMA Statement. PLoS Med 6(7): e1000097* n.d.)

4.1 Research Questions

The aim of this study was to identify the role of AI in recognising the onset of an emotional dysregulation event with the help of physiological signals and affective states of children. Therefore, the following research questions were formulated to carry out the literature review.

1. What modalities of data can be captured in children with ASC?
2. What are the most common machine learning methods used for detecting meltdowns in children with ASC?
3. Is there a need for a multimodal system?

4.2 Literature Sources

An extensive search of electronic databases focusing on studies conducted to detect distressing episodes in autistic individuals was undertaken. Inclusion and exclusion criteria were identified and used the aforementioned search terms. The following research databases were chosen to cover the research topic broadly.

Table 1: Database Sources

No.	Source
1	Scopus
2	ProQuest
3	Google Scholar
4	Science Direct
5	Springer
6	IEEE Xplore
7	Wiley
8	NTU Library OneSearch

Databases mentioned in table 1 were chosen on the following criteria:

– Covered topics related to computer science.
– Included studies on different aspects of the life of children with autism.

4.3 Search Keywords/Strings

The use of important and relevant keywords was necessary to ensure the efficient scoping of results and to avoid the inclusion of any irrelevant studies. The combination of keywords used to achieve this are as follows:

Meltdown OR Tantrum OR Challenging And Behaviour OR Aggression **AND**
Autis*(Autism or Autistic) OR ASC **AND**
Children OR Young Adults **AND**
Facial Expressions **AND**
Emotion Recognition **AND**
Physiological Signals **AND**
Multimodal Data **AND**
Machine Learning **AND**
Artificial Intelligence OR AI

4.4 Search Procedure

Literature for this study was selected in different stages.

Stage 1: All the relevant articles were extracted using the combination of strings mentioned in the previous section and saved using Zotero software for ease of use.
Stage 2: Duplicate articles were removed.
Stage 3: All article content was checked to make sure they were relevant to the literature review being conducted.
Stage 4: More articles were identified from the references mentioned in the above literature.
Stage 5: A final list of articles was drawn up to be included in the review.

4.5 Inclusion and Exclusion Criteria

Articles included in this review met the following criteria:

- The primary focus of the study was on rumble moments, meltdowns, tantrums, or challenging behaviours in children with ASC.
- The study employed artificial intelligence (AI) or other statistical approaches for data analysis.
- The research was published in the English language and conducted after 2015.

Studies with a strong emphasis on medical or biological aspects of children with ASC were excluded. This review specifically focuses on computer-science driven approaches to study emotions in autistic children. Researches that utilised non-invasive video-based analysis and sensor-based analysis were included as a part of this study whereas, articles which centred on medical tests and biological markers were excluded as they fall outside the domain of computer science. This may not have been an exhaustive review, however, it represents the majority of AI approaches being used in current research to detect the onset of an emotional dysregulation event.

5 Overview of Studies

Studies identified for this review (summarised in Table 2) broadly cover the identification of emotions and arousal in children with autism which can help in predicting the onset of an emotional dysregulation event that may happen in near future and alert the caretaker to minimise the trigger and prevent the situation from escalating. This will not only help in increasing the engagement rate of children while they are in the classroom as well as their emotional and mental well being leading to an overall improved quality of life (Turabee et al. 2023).

Literature shows a large variability in terms of methodological approaches used for detecting different sort of emotions which autistic children experience. In total 13 studies focused on using behavioural measures i.e., tracking facial expressions, audio and stereotypical motor movements of children while being given any sort of stimulus. The rest of the studies cover the use of a wide variety of physiological measures being used to detect the onset of distressing episodes before the child actually starts showing cues (Fig.4-a). Among these, the most common measures used to track any physiological changes in children are Heart Rate(HR) and Heart Rate Variability (HRV) extracted from Electrocardiography(ECG) signals. Moreover, Electrodermal Activity (EDA) signals also known as Galvanic Skin Response (GSR) or Skin Conduction(SC) are also used extensively in the literature followed by acceleration data (ACC). Fig.5-a shows the range of modalities of data covered in the studies selected answering research question 1. As seen in Fig.4-a, a very small portion i.e, 6 studies has made of use of multi-modal data i.e. combination of facial features, body movements and sounds made by children with autism along with physiological measures. Out of these, 2 of the papers analysed the data using statistical methods while 4 of the studies made use of deep machine learning models.

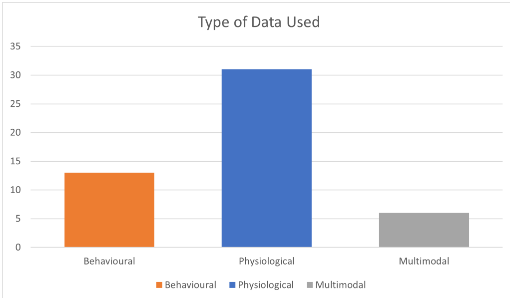

Fig.4(a) - Types of Data Modalities Utilized in the Reviewed Studies

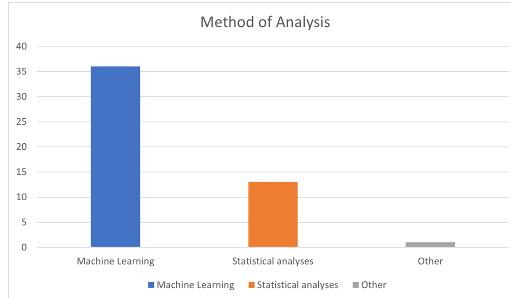

Fig.4(b) - Analysis Methods Employed in the Reviewed Studies

To answer research question 2, among the the literature under review, 36 studies used a range of machine learning methods to classify the emotional or arousal state of participants under observation from the multiple features extracted, while, 13 papers also performed statistical analyses (Fig.4-b). Support Vector Machine (SVM) is the most popular algorithm from supervised machine learning methods, and K-nearest neighbour (KNN) from unsupervised methods to classify affective states of children with autism. 23 papers used different sorts of deep learning methods such as Long Short-Term Memory (LSTM), Back Propagation Neural Networks (BPNN), Region-based Convolutional Neural Networks (RCNN), etc, while 5 used an ensemble of classifiers to obtain effective results (Fig.5-b).

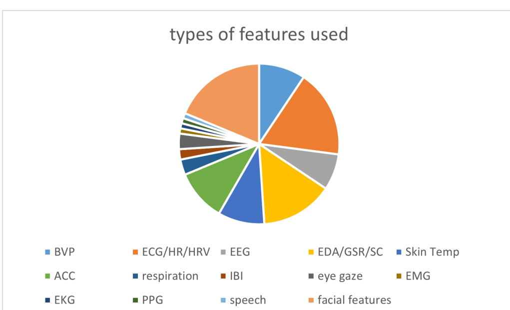

Fig.5(a) - Features Extracted and Utilized in the Reviewed Studies

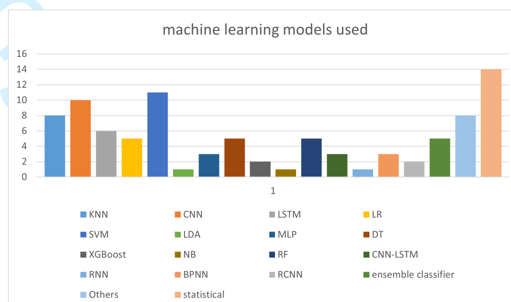

Fig.5(b) - Machine Learning Models Implemented in the Reviewed Studies

Table 2: Overview of Studies

Paper Reference	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(B. Anandhi et al. 2022)	5-11 years old,10 control group & 10 mild and moderate level of ASC children	closed room with a smart43-inch LED TV for displaying the cues	wearable Heart Wear ECG device	-	statistical, higher-order statistical (HOS) and geometrical features were derived from the ECG and HRV data	KNN and Ensemble classifiers	84.8% and 75.3% for control and test population respectively, using Ensemble classifier
(Hassouneh, Mutawa, and Murugappan 2020)	30 subjects for training 55 for testing and validation with a mean age of 22.9 years	participant sat in front of a computer that had a built-in camera	EPOC+ headset and a camera to record	six different emotional expressions (Ekman) expressed in a video sequence	Lucas-Kande optical flow algorithm for facial landmarks in real-time & EEG signals	CNN & LSTM	99.81% with CNN for facial landmarks & 87.25% with LSTM for EEG signals
(Kushki, Drumm, et al. 2013)	17 typically developing and 12 ASC children	signals sampled at a frequency of 256 Hz and recorded to a laptop	PPG sensor, Ag-AgCl electrodes, thermistor	Baseline task, an anxiety inducing task & computerized version of the Color Stroop (Color-Word Interference)	BVP, EDA, and skin temperature signals	Repeated measures analysis and post-hoc analysis	elevated HR with blunted phasic EDA during both baseline and anxiety, no in skin temperature in response to anxiety
(Goodwin et al. 2018)	20 children aged 6-17 years old with ASC diagnosis and minimally verbal	Sixty-nine independent naturalistic observational sessions	E4 by Empatica	-	ECG,EDA & ACC signals	Logistic Regression	Global prediction - AUC of 0.71 & Person-dependent prediction - AUC of 0.84
(Kushki, Khan, et al. 2015)	24 children with ASC	ECG time series sampled at 256 Hz	Wearable sensor	Color Stroop, Movie & Public speaking	ECG signals	Modified Kalman Filter	Sensitivity and specificity of 99% and 92% respectively
(Krupa et al. 2016)	20 children (10 with autism and 10 from control group) aged 3 to 12 years	-	wearable wristband	personalized stimuli e.g. playing a game, cycling to park etc	GSR and HRV	SVM	90% accuracy

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(Lucia Billeci et al. 2018)	20 ASC & 20 TD children aged between 18 and 36 months	ECG signals were recorded during an eye tracking joint attention task	SMI 500 Eye Tracking device, chest strap with smart sensor for ECG	watching some short videos reproducing three JA conditions	ECG signals	statistical analysis	increased SDNN and CV in toddlers with ASC at baseline and LF during the task
(Sarabadani et al. 2020)	15 children aged between 12 and 18 years with clinical diagnosis of ASC	participants positioned in front of a laptop, and viewed the emotional stimuli	Procomp Infiniti data acquisition system	viewed standard images known to evoke varying levels of valence & arousal	ECG, SC, respiration, and skin temperature	ensemble of classifiers	high/positive state from a high/negative state-78.1%, low/positive state from a low/negative state 84.5%
(A. Alban et al. 2023)	5 male children with autism, aged between 7 and 10 years	social robots and regular children's toys used as stimuli	wristband wearable sensor Empatica E4	-	ACC, EDA, Temperature, HR, BVP	SVM, MLP, DT, XGBoost	SVM – 85%, MLP – 97%, DT – 98%, XGBoost - 99% accuracy
(Cheung et al. 2016)	10 TD & 5 ASC children aged 8–13	physiological signals sampled at 256 Hz	ProComp Infiniti data acquisition system and Biocomp Infiniti software	listening to relaxed state and anxiety provoking music	EDA, skin temperature, BVP and chest (respiration)	statistical analysis	classification accuracy, sensitivity, and specificity - 80.8% , 84.9%, 76.8%
(Puli and Kushki 2020)	15 children and youth with a diagnosis of ASC aged between 8 and 16	accelerometer and ECG signals were sampled at 250Hz	Shimmer 2r sensor	Stand still, slow walk and then walk at fast pace with a baseline and a stressor activity	HR	Multimodal Kalman Fitlter	overall arousal detection accuracy of 93%
(Chiu et al. 2016)	40 children with ASC aged 8-18 years	-	wearable, wireless biophysical sensor	StroopColor-Word Interference Test	ECG Signals	Classification and Regression Tree (CART),LR , SVM, NB, & KNN	80% classification accuracy
(Helminen et al. 2017)	12 children with ASC, 17 TD, and 16 DD children aged 2-5	-	Tobii Studio 3.2.1 Net Station 4.5.1	series of computerized tasks	HR, EEG, and eye movements	statistical analyses (ANOVA)	P=.004 enhanced HR orienting response to direct gaze compared to averted gaze in low-functioning children with ASC

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(A. Q. Alban et al. 2021)	Ten year old male child with autism	-	Empatica E4 wristband	different toys and two social robots as stimuli	ACC, EDA, IBI, TEMP, HR, BVP	SVM, MLP, DT	Accuracy – 97% specificity, recall – 97% Precision - 0.91
(Silva et al. 2021)	Dataset FER+	-	-	-	labelled images	Inception-Resnet-v1 & KNN	Train - 81.6% Test - 80.6%
(Jarraya, Masmoudi, and Hammami 2021)	Meltdown Crisis	-	Kinect V2	-	videos dataset	RF & Inception Resnet V2	RF-91.27%, InceptionResnetV2-97.5%
(Al-Rammah, Masmoudi, and Jarraya 2022)	Meltdown Crisis	-	-	-	video dataset	CNN-LSTM	98% recall and F1 Score
(Jarraya, Masmoudi, and Hammami 2020)	-	-	Kinect V2	-	videos dataset	Feed Forward (FF),Cascade Feed Forward (CFF),RNN & LSTM	RNN - 85.8%
(Chu et al. 2018)	15 HFA students aged 8–12 years	-	Webcam and computer	participated in two-stage mathematics e-learning exercises	video dataset	SVM	92.40%
(Pal and Rubini 2021)	COCO dataset	-	-	-	images with 17 pose key point co-ordinates	person pose estimation with RF	83% - precision and 71% - recall
(Bonacini, Mahmud, and D. J. Brown 2023)	children with autism	-	-	actions that pre-empt the onset of a meltdown	video data	LSTM	90% on a 147 actions validation set
(Val-Calvo et al. 2020)	6 volunteers (5 male, 11 female) aged 19-40	-	GePHYCAM, Empatica E4 wristband, Open BCI EEG Cap	watching audio-visual resources	facial expressions & physiological signals	CNN and Ensemble classifier	higher than 80% on average for arousal and valence
(Matthews et al. 2019)	19 neurotypical users and 19 users with autism	captured pupillary response, fixation location, and fixation duration	Gazepoint GP3 video-based eye-tracker	browsing and synthesis of web pages	eye gaze data	Scanpath Trend Analysis (STA)	lower arousal response to affective contents in individuals with autism

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(Nuske et al. 2019)	41 children with autism aged 2- to 4-years	-	Biopac BioNomadix ECG and accelerometer	everyday life experience with positive and negative emotion	HR	statistical analysis	22 ± 16% HR increase from baseline 58 ± 22 seconds before the onset of a challenging behaviour
(Krishnappa Babu and Lahiri 2022)	10 individuals with HF-ASC (5 males and 5 females)	-	ViewPoint eye tracker	VR-based tasks	eye-gaze data	statistical analysis (t-test)	increased fixation duration
(Di Nuovo et al. 2018)	6 children diagnosed with ASC and Intellectual Disability	-	Softbank Robotics Nao v4	execution of the rehabilitation tasks	video data	NB, KNN, RCNN, R–CNN with HOGs and K–NN, MTCNN, MTCNN with HOGs and K–NN	MTCNN with HOGs and K–NN – 88.2% accuracy
(Piana et al. 2021)	10 children with HF Autism mean aged 9.6 years old	-	Kinect v2 sensor	playing serious game	kinematics and video streams	ANOVA	increase of recognition accuracy, $p<0.05$ and gradual increase of expression accuracy
(Deschamps et al. 2015)	20 children with ASC aged 6-7 years and 27 TD children	EMG signals filtered offline (high-pass 20 Hz, 48 dB/ octave)	ActiveTwo system (BioSemi)	cartoon character was presented during an emotional film clip	facial EMG	Anova and t-test	reduced sensitivity to distress signals in children with ASC
(Legiša et al. 2013)	8 children aged 8–14 years with HF autism and 8 age-matched typically developing controls	eight odors were used in this study	-	-	facial responses, HR and skin conductance response (SCR)	KruskalWallis test, Chi-square tests, Wilcoxon signed-rank test, Pearson coefficients	difficulties in how the HFA children report their emotional reactions that matched their facial expression
(Di Palma et al. 2017)	5 children with HF-ASC (all males, age range = 6-8 yrs)	-	chest belt for ECG signal acquisition	serious games with imitation (IM) and joint attention (JA)	HR, RMSSD & RSA	qualitative data analysis and quantitative analysis	decrease in RMSSD and RSA, and engagement of the children during sociocognitive tasks

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(Xiao et al. 2020)	eNTERFACE'05 dataset and Fer2013 dataset	firstview emotional care system for children with ASC (First-ECS)	-	-	body temperature, oxygen content in blood, EKG index, and EEG signal with facial data and voice data	Qualitative data analysis and Quantitative analysis, Alex-Net deep CN for voice data, VGG-Net network for face recognition	Both models performed very well in emotion recognition from the aspect of a dataset
(Patnam et al. 2017)	data was acquired from various databases and reliable internet sources	-	-	-	raw pictures and videos	deep RCNN	validation accuracy of 93% & testing accuracy 92%
(Khullar, Singh, and Bala 2021)	-	Data recorded from the wristband	-	-	HR, skin temperature, and GSR	CNN, LSTM, and CNN-LSTM	CNN-LSTM training and testing accuracy of 96%
(L. Billeci et al. 2016)	5 children with ASC aged 6–8 years	-	Enobio wireless device wireless ECG chest belt	children interacted with the examiner and played with different objects	QEEG, HR, HRV & recorded videos	statistical analysis	increase in coherence during engagement
(Bian et al. 2016)	4 teenagers with ASC	-	Logitech G27 driving controller	driving assignment in VR	PPG, GSR and RSP	Random Forest	higher engagement characteristics for a majority of the task duration
(Rad and Furlanello 2016)	6 participants with autism in a longitudinal study	-	3-axis wireless accelerometer	body rocking, hand flapping, or simultaneous body rocking and hand flapping	ACC	CNN and Transferred-CNN	F1-Score Study1-0.7, Study2-0.5
(Montassar, Chikhaoui, and Wang 2023)	9-years-old male child with autism	-	Empatica E4	-	BVP, EDA, ACC	SVM, RF, XGBoost & TabNet	Accuracy with XGBoost – 80%
(Amiri et al. 2017)	12 healthy participants aged between 23–33 & 2 with diagnosed with autism ages 15 & 16	-	Moto360 SmartWatch	hand flapping, painting, and sibbing	ACC	ensemble of 40 decision trees	accuracy 94.6%

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(Villanueva et al. 2022)	videos with activities classified by activity recognition with the corresponding labels of classes and ESC-50 dataset	-	web camera, Re Speaker 2-Mics Pi HAT	-	audio and video data	squeezeNet and transformer algorithm	98.33% accuracy
(Akinloye, Obe, and Boyinbode 2020)	one male with 7 years of age	affective-based e-Healthcare system	-	activities during therapy session	EDA & speech recognizer sensors	fuzzy inference system	92.07% accuracy
(Mishra and Welch 2023)	6 male participants aged between 10.4-11.9 years	-	Empatica E4 wristband	-	BVP	LSTM, CNN and CNN+LSTM	CNN+LSTM - 95.5% accuracy
(Saranya and Anandan 2022)	AFFECTNET datasets and Kaggle Facial Autistic Datasets-2019	Facial Action Coding Systems (FACS)	-	-	facial features	FACS-CNN and hybrid Deep Learning of LSTM	MLP-48.67%, CNN-67.75%, & LSTM-71.56%
(Anandhi and Jerritta 2021)	15 controls and 15 children who have ASC aged 5 to 11 years	-	-	favourite and unfavourite audio- and audio-visual stimuli taken from internet source	QRS complex derived from ECG signals	KNN & Ensemble learner	Ensemble learner - accuracy of 75.5% in controls, 70.5% in children with ASC
(Redd et al. 2020)	5 children aged between 8 and 12	-	Empatica E4 wearable sensing system	-	BVP, EDA, HR, IBI, TEMP data & acceleration data	LR, SVM, DT	global model mean accuracy 68% for LR and SVM, and 63% for DT, person-dependent model mean accuracy up to 85%
(Mohammadian Rad et al. 2018)	6 participants with autism in a longitudinal study	-	three 3-axis wireless accelerometers	engaged in body rocking, hand flapping, or simultaneous body rocking and hand flapping	ACC	three-layer CNN architecture	ensemble of LSTM learners provided accurate and stable SMM detector

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Paper Ref	Participant Information	Context/settings	Equipment Used	tasks performed	Elicitation Method	Type of Analysis	Results/Findings
(Zaman et al. 2022)	30 ASC children aged 5 to 13 years	-	head gear with Brainwave acquisition subsystem (BAS) and the Location tracking subsystem (LTS)	three instances: positively excited, neutral, and negatively excited	EEG	two ensemble models KLRE and ALRE	KLRE - 89% accuracy and 0.90 F1-score , ALRE - 93% accuracy and 0.93 F1-score, Overall system accuracy- 92% in predicting the emotional status of the child
(Banire et al. 2021)	46 children (ASC=20, TD=26)	-	webcam	different attentional tasks that simulate CPT	video data	geometric feature transformation using SVM classifier and time-domain spatial features to 2D spatial images using CNN	SVM training (ACC=99.5%) and testing (ACC=95.9%, AUC=0.965)
(Masino et al. 2019)	38 participants (22 ASC, 16 non-ASC)	-	consumer-grade electrocardio-graphic sensor	data captured during rest and during activities designed to mimic stress	HR & RR interval measurements	LR & SVM	SVM - 93% LR - 87% accuracy
(Siddiqui et al. 2021)	10 autistic children	-	Hexiwear sensor module consisting of both an accelerometer and a gyroscope	subject produced gestures for 24 activities performing each gesture about 10 times	gestures	KNN, DT, NN & RF	Highest accuracy – 91.96 using dataset cross-validation and leave-one-person-out cross-validation
(Bellato et al. 2022)	106 Children aged 7-15 years diagnosed with or under clinical assessment for autism and/or ADHD	-	The Hexoskin SWS	3-min resting-state period, a ‘passive’ auditory oddball task and an ‘active’ response conflict task	HR	statistical analyses	reduced activity of the PNS and hyper-arousal during passive and active tasks

6 Discussion

A wide range of research has been undertaken for the identification of cues which a child exhibits before and during the episodes emotional distress. Pre-emptive detection can assist parents, teachers and caregivers in deploying early intervention and prevention strategies to help mitigate the effects of dysregulation events. This review explores studies conducted around behavioural changes in children with ASC and how they can be minimised for improved emotional awareness and engagement with the environment.

Across the reviewed studies, the gender representation is under-reported, with limited or no information on the male-to-female distribution of participants in experimental research. Given the diagnostic gender bias in autism research—where girls who meet the criteria for ASC are at a disproportionately higher risk of not receiving a formal diagnosis(Loomes, Hull, and Mandy 2017), it is possible that these studies have not adequately captured gender diversity. As a result, their findings may reflect a male-dominated sample. This limitation reduces the generalisability of the findings to the broader autistic population, particularly to females, who may present with distinct characteristics and challenges.

Behavioural and physiological data are the two most common modalities used in the literature for the detection of emotional dysregulation in children with ASC. As discussed in response to research question 1, behavioural responses of children with autism can be collected in the form of videos of facial expressions and body movements along with audio data while, physiological data may include body signals such as pulse rate, body temperature, blood pressure, respiration rate etc. This data is then fed to machine learning models, as discussed in research question 2, for the prediction of the affective state of autistic children. Focusing on tracking facial expressions, atypical sounds or stereotypical motor movements, can mean however that by the time challenging behaviour is predicted, a child might already be at the onset of a meltdown event, thus making it difficult to de-escalate the situation. Similarly, not every child may tolerate the use of wearable devices for the collection of physiological data as it may create an unfamiliar tactile sensation and cause sensory overload. Considering the varying tolerance levels of children with autism, there is a need for multi-modal systems (physiological signals in combination with behavioural data), which cater to different kinds of data given the sensitivities associated with ASC(Turabee et al. 2023). Statistics also show that a very small portion of studies reviewed has used multi-modal data for the inference of rumble moments and preceding episodes of emotional distress (Fig.4-a) answering our third research question.

A wide range of models have been employed in the literature, from traditional machine learning techniques to more complex neural networks, with varying levels of performance and explainability in the real-world scenarios. Traditional models such as Logistic Regression (LR), Decision Trees (DT), and Random Forests (RF) are reliable, robust to overfitting, and handle noisy data well. However, given the complexity of the data used in these studies, such as images, videos, and physiological signals, these models exhibit variability in their results, suggesting limitations in capturing intricate data patterns. On the other hand, neural networks, particularly CNNs, RNNs, and hybrid models like CNN-LSTMs, have higher accuracies often exceeding 90%. They effectively process high-dimensional data but have low interpretability, making it difficult to explain their predictions. Additionally, their performance is heavily dependent on large datasets, which is a notable limitation as the reviewed studies used relatively small datasets. While traditional models offer better explainability and robustness, their applicability to complex data is restricted, whereas deep learning models provide higher accuracy but require extensive data and lack transparency. Therefore, selecting the appropriate algorithm requires a careful balance between the complexity of the problem, the nature of the data, and practical constraints in real-world applications. This highlights the need for eXplainable Artificial Intelligence (XAI) for the early prediction of rumble moments in children with autism - an unexplored domain. The use of XAI models will help parents, teachers and caregivers in understanding why a certain prediction was made by the model at the human-level, thus making systems designed for the inference and de-escalation of emotional dysregulation events in autistic children more readily adopted.

Another gap identified after reviewing all the studies selected for the purpose of this literature review is the lack of availability and accessibility of standard data sets to study challenging behaviours in children with autism. The majority of the studies reviewed have used a small number of participants to collect data under different contexts and settings. This leads to lack of generalisability and transferability, i.e. different approaches and results are not comparable. Additionally, feature representation learned from one data set cannot be used for the benefit of other data sets. Data used in a number of studies is also highly skewed. Most of the studies reviewed have only given details on the autistic group and no details of control group are given causing the the data set to be imbalanced and biased. Moreover, due to the small number of samples in the data set, there is a risk of over-fitting. The machine learning models in use might adjust excessively to the data thus making it ineffective for use on other scenarios and data sets.

The aforementioned problems concerning small data sets can also be dealt with using various techniques in machine learning. Imbalanced data sets can be balanced by using synthetic samples also known as oversampling. SMOTE (Synthetic Minority Oversampling TEchnique) and Asymmetric Loss function are the common techniques used for this purpose. Similarly, the issue of a small number of samples can be compensated by generating more data using methods such as Generative Adversarial Networks (GAN's) and Data Augmentation. Moreover, using a combination of multiple models with different hyperparameters can also help in increasing the generalisation of the model resulting in better predictions (*Techniques and pitfalls for ML training with small data sets* 2023; *Dealing with very small datasets* 2023).

To address the issue of limited accessible and standardised datasets for studying engagement and arousal in children with autism, we curated our own dataset as part of an Erasmus+ project AI-TOP-2020-1-UK01-KA201-079167 (**AI-TOP**). The aim of this project was to develop a multimodal platform capable of predicting behavioural states such as engagement, bored and frustrated of autistic children in classrooms settings, as well as detecting early signs of emotional distress. Nottingham Trent University collaborated with Nottingham City Council Special Education Needs and Disability(SEND) Team and visited 5 different schools to collect the data.Video recordings of 39 students were gathered across 74 sessions while they played computer games based on the 'Continuous Performance Test' (CPT) (Taheri, D. Brown, and Sherkat 2020; Rahman et al. 2022) in over 74 sessions. All children involved in the data collection were either formally diagnosed with ASC, undergoing the diagnostic process, or had a suspected ASC diagnosis reported by parents or teachers. The recorded videos were labelled with corresponding behavioural states using an observational checklist created by experts in Autism from the Nottingham City Council Autism Team.

To enhance the reproducibility and generalisability of this dataset, it has also been made available on Kaggle as an anonymised 3D cloud point dataset. Facial and pose landmark detection was performed on these videos to produce a dataset that captures data points when a child is in a particular state of arousal or engagement in learning (e.g. smiling, calm, yawning, rocking, eyes on or off screen, etc.). This dataset will aid in predicting the onset of emotional dysregulation events, enabling early interventions to reduce distress for the child and minimize disruptions in the classroom environment.

7 Future Directions and Limitations

As the 3D cloud points dataset is now publicly available, our primary focus moving forward is to leverage this dataset for training various machine learning models aimed at predicting behavioural and emotional states of children with ASC. Prediction of 'meltdown' moments at a very early stage can help parents, teachers, and caregivers support the emotional and mental well-being of children via early intervention and improve overall quality of life. Moreover, development of generalised models that would assist autistic individuals in comprehending the triggers associated with their Autism is also an important and impactful area of future research.

Another promising area for future work involves the integration of multi-modal data. Using data from diverse sources such as visual, auditory, and physiological signals offers the potential for richer insights into the emotional and behavioural states of children with ASC. While integrating multimodal data into platforms has significant benefits, it also presents several challenges. The increased dimensionality resulting from the inclusion of various data modalities makes the system more complex, and integrating information from different data streams, known as fusion, becomes increasingly difficult. Furthermore, the temporal context must be maintained during this integration to ensure the reliability and accuracy of predictions. Each modality of data brings its own set of noise, which can complicate the analysis and potentially affect the overall effectiveness of the model. There are a number of trade-offs to be considered when developing multimodal platforms to be deployed in the real-world scenarios. For example, adding more data streams to a system gives greater insights from the multiple features but also increases the complexity of the model. Striking the right balance between performance, robustness, and system complexity remains a significant challenge (Liang, Zadeh, and Morency 2022; Gaw, Yousefi, and Gahrooei 2022).

8 Conclusion

Autistic children show distinguishable cues before the emotional transition (rumble moments) and during emotional dysregulation (meltdown event), which can be used for the timely mitigation and avoidance any the undesirable effects of emotional dysregulation - to the child themselves in terms of anxiety and mental wellbeing, and the wider classroom environment. To achieve this objective, a number of research studies have been taking place in the recent past to identify the precursors of emotional dysregulation which might be exhibited by an autistic child before becoming overwhelmed or distressed. Early identification and evidence-based well-being intervention can help in increasing engagement with surroundings and the overall quality of life of children with autism. The aim of this review was to analyse the different methodological approaches used in the literature for the detection of challenging behaviours in children with ASC. Studies were extracted from multiple electronic databases and explored to answer the research questions posed, assess the potential scope of research on the topic under consideration, and to identify gaps in the existing literature.

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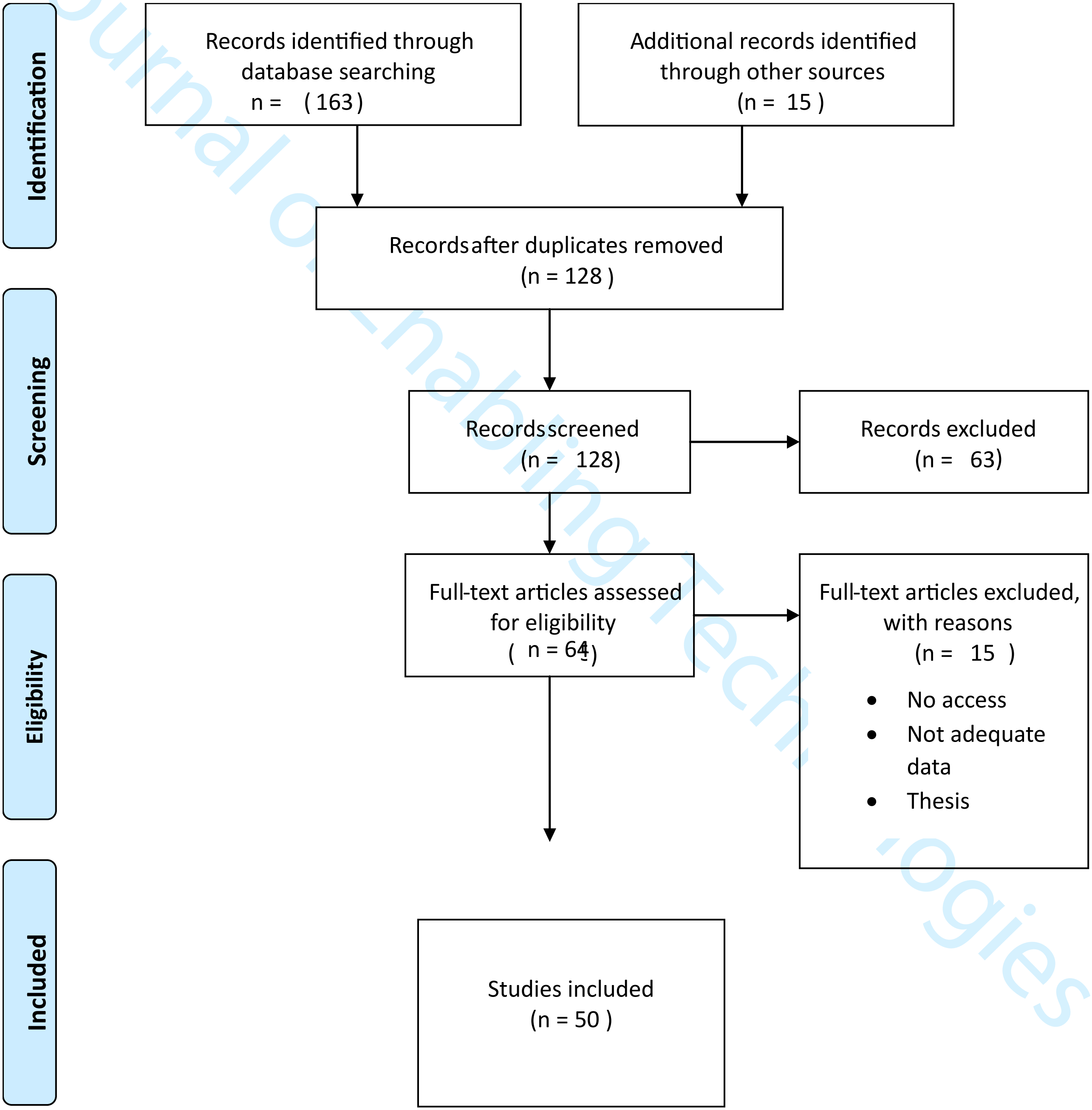
Reviews/Comments	Action taken	Page No.
Complete Fig.4 and Fig.5. (Example: Fig.4 - ....)	Made corrections	Figures on page 9
You can add greater detail to your methodology and clarify the inclusion/exclusion criteria.	Extended the inclusion exclusion criteria and added more details	Page 8
Originality and Contribution: The manuscript claims to be the first scoping review focusing on this topic. While the claim is compelling, it would benefit from a clearer justification. For instance, the authors could briefly mention similar works (if any) and explicitly state how this review adds value beyond prior studies.	Have added similar works and compared on how this study adds value i.e.. it is a comprehensive scoping review of machine learning and statistical approaches used in detection of emotional dysregulation events in children with ASC, incorporating wider range of modalities.	Added to the end of introduction page 2/3.
Methodology: - The use of the PRISMA extension for scoping reviews is appropriate and well-documented. However, the inclusion and exclusion criteria could be elaborated further. For example, why were studies focused on medicine or biology excluded? Some of these might contain relevant findings on physiological signals that intersect with AI approaches. - The review omits a detailed description of how bias was mitigated during study selection. Adding a brief section on inter-rater reliability or cross-validation of the selected studies would enhance transparency.	Extended the inclusion exclusion criteria and added more details To make sure there was no bias in the selection of literature for the review, following steps were taken: 1. Made sure that the methodology is transparent. Clearly documented the research question, inclusion/exclusion criteria, and search strategy to ensure reproducibility and transparency. 2. Added a Conflict-of-Interest Disclosure. 3. Have critically appraise included studies to identify potential weaknesses. 4. Used **flowchart (PRISMA-ScR)** to document the selection process.	Page 8
Critical Analysis of Reviewed Studies:	Discussion section has been revised to add the following:	Discussion section-page 17(highlighted in the pdf version)

- The manuscript largely summarizes findings from reviewed studies but lacks a deeper critique. It would be valuable to assess the limitations, biases, or methodological weaknesses of the studies. For example, did the reviewed works adequately consider diversity in autism presentations? - Highlighting how different machine learning approaches compare (e.g., neural networks vs. traditional statistical methods) in terms of accuracy, reliability, and applicability to real-world settings would improve the discussion.	- Added more critique related to limitations of the studies under review such as gender representation, choice of machine learning models vs dataset size, use of single mode of data vs use of multi modal data. - Addressed how the identified gap i.e lack of explainablilty in ML models can be dealt. - Techniques in machine learning to deal with small datasets.	
Multimodal Data and Accessibility: While the need for multimodal systems is emphasized, the challenges associated with integrating such systems (e.g., data fusion, real-time processing, computational complexity) are not discussed. Providing a balanced view of their feasibility would enhance the manuscript's practical relevance.	Added a separate section of future directions and limitations and elaborated on this.	Page 19
Reproducibility and Generalizability: The lack of accessible datasets is noted as a gap, but the implications of this on reproducibility and scalability of proposed solutions need further exploration. Could the authors suggest strategies to overcome this limitation, such as open data initiatives?	Mentioned about creating our own dataset and covered on how problems concerning small data sets can also be dealt with using various techniques in machine learning	Last 3 paragraphs on page 18
Clarity and Readability: - Some technical terms (e.g., "rumble moments," "interbeat interval") might require more accessible	Clarified the definition of rumble moments, inter-beat interval and changed the caption of Plutchik's wheel of	Rumble moments: page 2 Inter-beat interval: last paragraph on page 4

definitions or explanations for readers unfamiliar with these concepts. - Figures such as Plutchik's Wheel of Emotions (Figure 1) are informative but could benefit from a brief explanation in the figure caption.	emotions figure.	Plutchik wheel of emotions figure: page 4
References: While the manuscript cites relevant studies, some references (e.g., "Autism 2017") are vaguely formatted. Ensure all citations follow the journal's prescribed format and include complete details.	Corrected the reference	Page 1
Future Directions: The manuscript briefly mentions future research opportunities. Expanding on this section to provide specific recommendations (e.g., potential AI algorithms, types of wearable sensors) would strengthen the practical utility of the review.	Added a new section on future directions and challenges and talked about limitation of multimodal platforms.	Page 19
Typographical Errors: There are minor typographical errors and inconsistencies (e.g., capitalization of terms like "Artificial Intelligence"). A thorough proofreading is recommended.	Paper was proofread and all the mistakes were corrected.	

PRISMA Flow Diagram for the scoping review process



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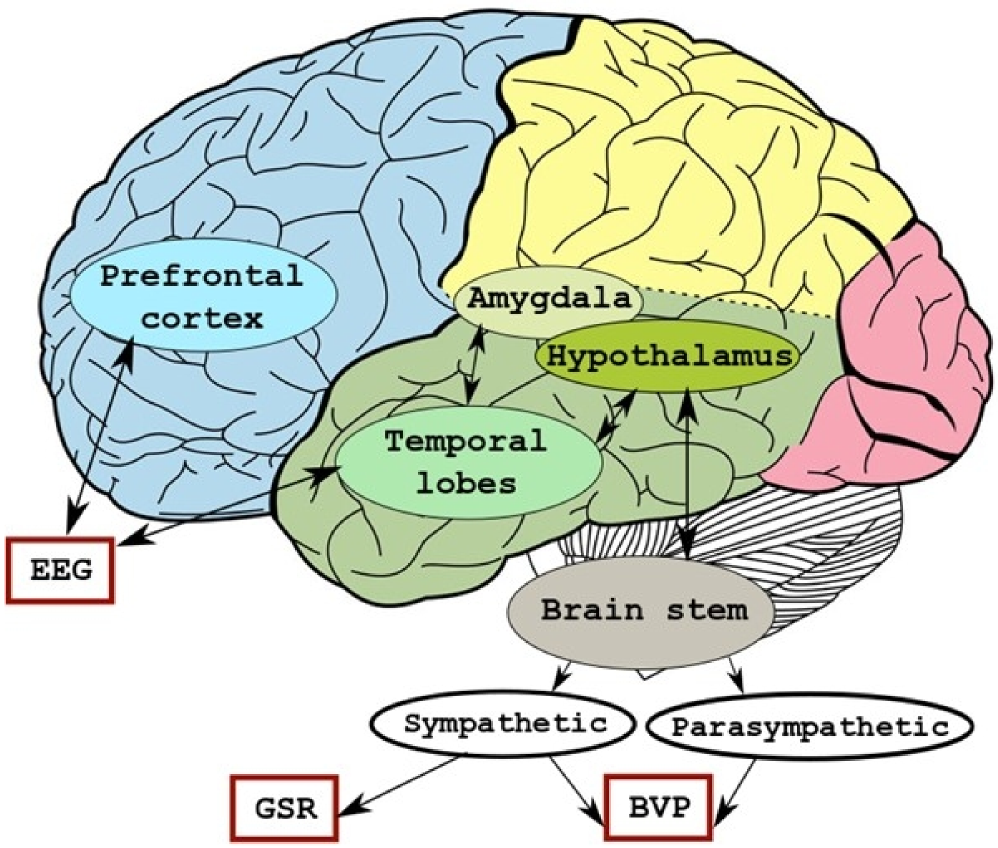

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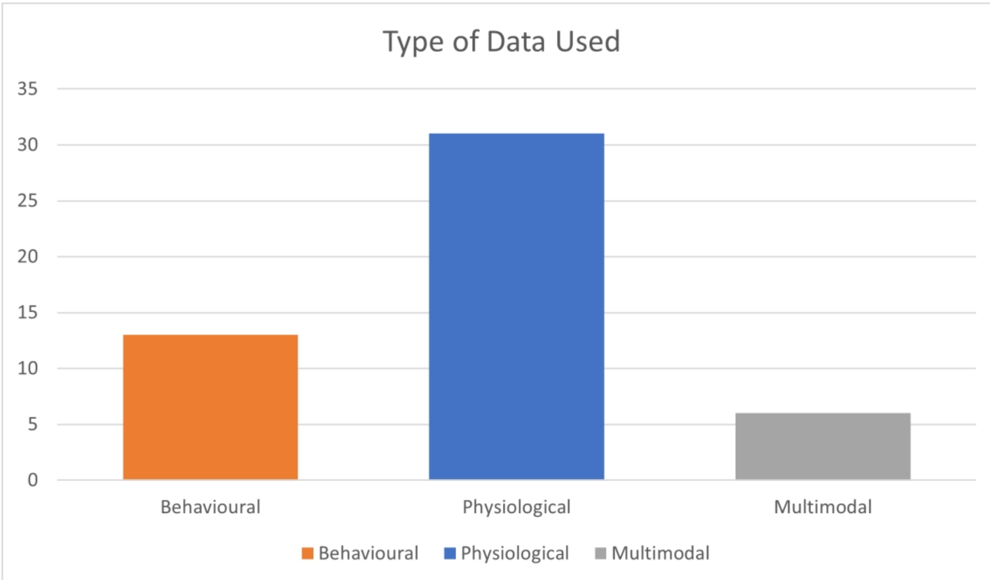

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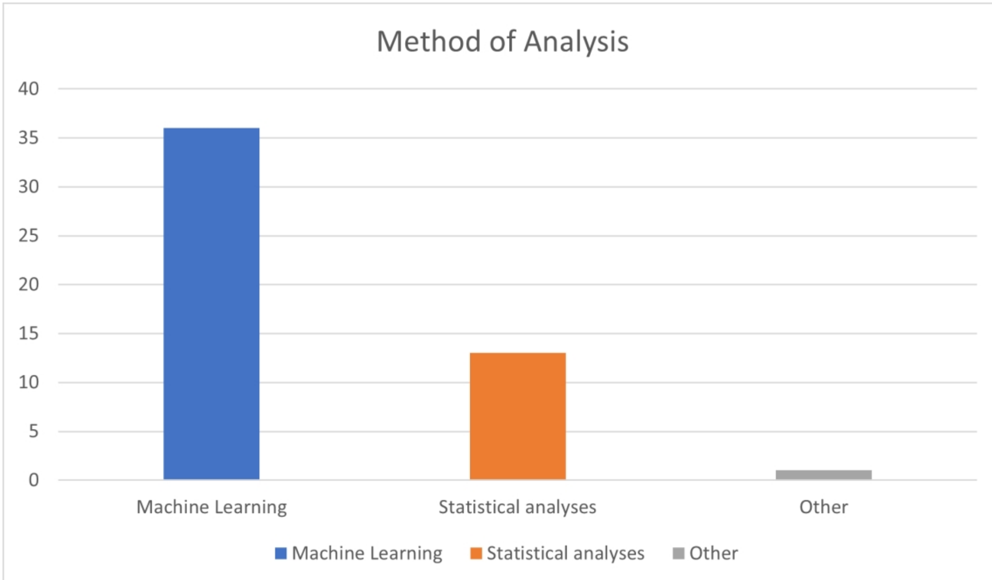

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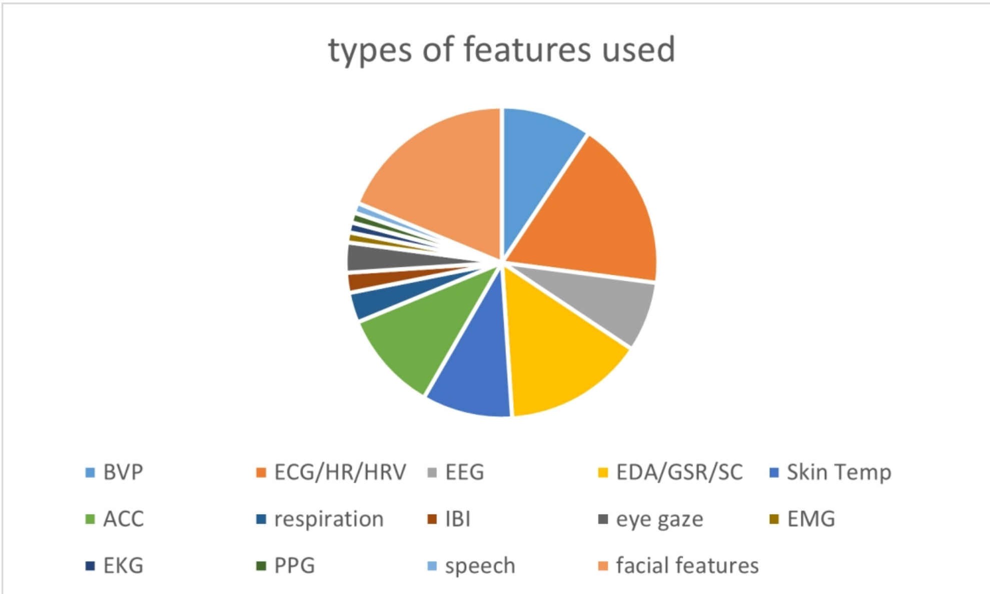

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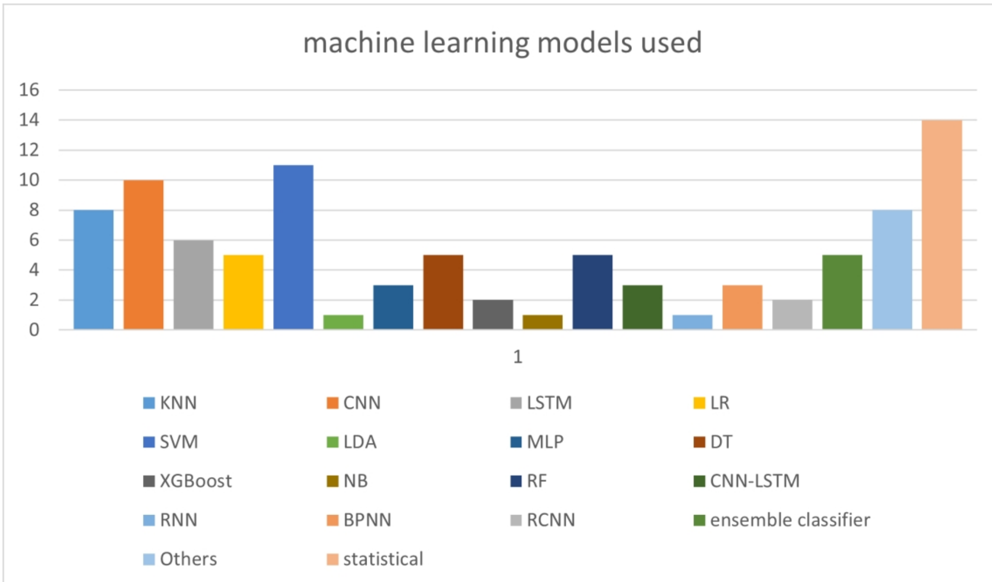

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