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A Physiological Approach to Affect Recognition in Children: Insights from EDA

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Abstract

Objectives: This study aimed to develop an automated approach for detecting affective states in typically developing children by analyzing their electrodermal activity (EDA) and addressing the challenges and significance of emotion recognition through physiological signals. **Method:** The study involved 15 children aged 8–12 years whose multimodal emotional responses were recorded using an EmotiBit device during emotion elicitation via short video sequences. Key characteristics were derived from EDA signals using discrete wavelet transform, and classification was executed using a Multilayer Perceptron (MLP) network. **Findings:** The proposed method achieved an accuracy of 80% in a three-class emotion classification task, demonstrating its effectiveness in recognizing the affective states. **Novelty:** The proposed methodology has the potential to facilitate the development of sophisticated and intelligent systems that can accurately recognize emotions in typically developing children by using electrodermal activity.

Keywords: Emotion recognition; Electrodermal activity (EDA); discrete wavelet transform; machine learning; children; Multilayer Perceptron (MLP)

1 Introduction

Physiological signals include electroencephalography (EEG), electrocardiography (ECG), and electrodermal activity (EDA), which provide a foundational understanding of emotions in affective computing[(1)]. However, these are not widely used in children. Although studies in adults have demonstrated that the use of multimodal approaches (e.g., EEG combined with facial expressions[(2)] or EEG, GSR paired with ECG[(3)])increases the accuracy of emotion classification, these methods are subject to limitations when applied to children. Children may not be as able as adults to report subjective feelings (cognitively or verbally), and if they are, they may not be as reliable as their reporting. Furthermore, these approaches rely on invasive configurations (e.g., multi-electrode EEG) or adult-specific data (DEAP, AMIGOS, MAHNOB-HCI, CASE, ASCERTAIN, and WESAD)[(4)], which limits their scalability to pediatric subjects. Child emotion recognition still prioritizes facial expressions[(5)] or speech[(6)] despite their variability in young populations[(7)]. Although EDA[(8)] shows promise for pediatric applications (e.g., SVM-based toddler studies[(9)]), no study has addressed typically developing children using wearable-compatible EDA analysis.

We bridged these gaps by introducing an automated EDA-based classification framework for children, leveraging a novel dataset (15 subjects) collected via wearable Emotibit[10]. We filled these gaps by presenting an automated EDA-based classification pipeline for children using a new dataset (15 participants) obtained through the wearable system Emotibit. These limitations include (1) the absence of an EDA dataset for children, (2) the dependence on expensive and complex devices, and (3) the necessity of scalable, non-invasive solutions. Our methodology, results, and conclusions are presented in Sections II–IV.

2 Methodology

The following section provides essential details regarding the study's participants, stimuli selection, sensors employed, and proposed approach.

2.1 Participants

Data were collected for the research study from a group of 15 typically developing children, randomly selected from a population of 8–12 years old. All children participating in the study had normal vision and hearing. Written informed consent was obtained from all parents/guardians, and age-appropriate verbal or written consent was obtained from all participants. table 1 illustrates the participants' demographic and experimental characteristics.

Table 1. Participant demographics and trial characteristics

Participants	Total	Age (Mean $\pm$SD)	Mean Valid Trials per Participant	Duration of video
Boys	7	8.6$\pm$1.3	8	1-3 min
Girls	8	8.5$\pm$1.3	8	1-3 min

2.2 Experiment Design

Research on emotion recognition requires two essential considerations: suitable stimuli and appropriate sensors. These factors are crucial for obtaining reliable findings.

2.2.1. Stimuli Selection and Validation

As part of our experimental study, we aimed to induce pleasant, unpleasant, and neutral emotions in typically developing children by exposing them to different visual stimuli. In the present era of digitization, children are usually influenced by a vast array of content on platforms, such as YouTube. The content that they encounter significantly affects their beliefs, values, and conduct. Short videos on social media have a powerful impact on children[11]. Therefore, we utilized short videos for emotion recognition tasks, with two steps in the selection and validation processes:

2.2.1.1. Initial Selection: . We manually selected two distinct video categories. In the first category, we utilized a combination of funny video clips (n=8) featuring diverse individuals and animals to induce positive (pleasant) emotions, whereas in the second category, we disturbed scenes from popular movies to trigger negative (unpleasant) emotions (n=8). These videos were sourced from social media platforms. For the neutral condition, we guided the children to sit comfortably before proceeding with the signals.

2.2.1.2. Pre-validation:. Selected short videos were initially presented to a separate group (n=5) of typically developing children (who did not participate in the main EDA study). We carefully evaluated and analyzed their feedback and self-assessment, which led us to consider these videos as suitable for our research.

Based on this pre-validation, the class label for each EDA trial in the main experiment was determined according to the designated and validated emotional category of the video: pleasant, unpleasant, or neutral.

2.2.2. Sensor

Another important aspect of studying emotions in children is the use of sensors that are comfortable for them. We used an EmotiBit wireless easy-to-wear sensor, which captures high-quality physiological, emotional, and movement data, to make the study comfortable for children. EmotiBit includes an EDA sensor, multi-wavelength PPG, medical-grade temperature sensor, and a 9-axis IMU sensor. In this study, we only considered the EDA data. Emotibit can be easily placed on different body parts for flexibility and user convenience[12]. In our study, we placed the sensor on a child's wrist, similar to a traditional watch. After attaching the sensor, we took baseline recording of 1-2 minutes. Participants were asked to sit in a relaxed position during the initial recording. The primary goal of the baseline condition was to achieve a neutral emotional state while monitoring the physiological signals. During the study, each participant underwent two sessions with a neutral sequence of 50 seconds in between, followed by a video sequence presentation. A timeline of the experimental paradigm is shown in Figure 1.

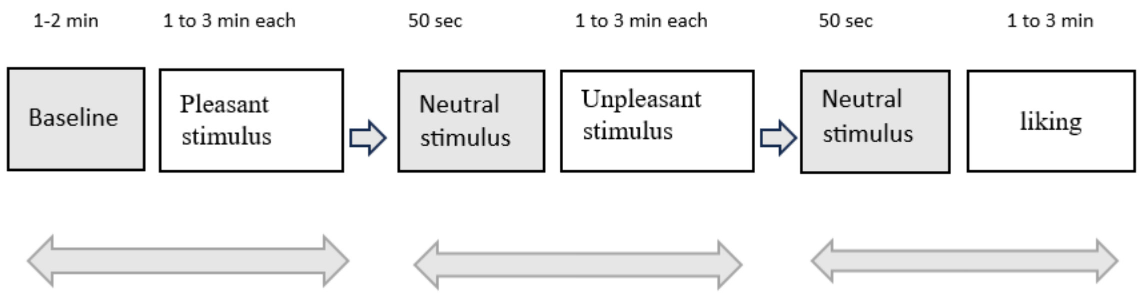

Fig 1. Timeline of experimental paradigm

2.3 Proposed emotion recognition approach

Most theories of emotions highlight the significance of physiological responses in determining emotions. One technique for measuring this is through EDA, which gauges variations in electrical conductance caused by perspiration to indicate levels of physiological arousal. EDA, also called galvanic skin response, is a physical response that shows how active the sweat glands are under the control of the visceral motor system (autonomic nervous system). The sympathetic nervous system affects EDA by influencing sweat gland activity according to one's emotional state(13). Although EDA is a standard measure of arousal rather than valence, we propose that within the framework of validated stimuli, unique patterns of phasic EDA (such as the frequency and amplitude of skin conductance responses) demonstrate systematic variations across categories(4),(14). We expected that both Pleasant and Unpleasant videos, as high-arousal stimuli, would provoke more pronounced EDA responses than low-arousal neutral stimuli.The following section describes the three-fold process of the proposed approach: preprocessing, feature extraction, and classification.

2.3.1. Preprocessing

The electrodermal activity (EDA) signals were preprocessed using a bandpass filter with a frequency range of 0.01–5 Hz to minimize noise and remove slow drifts and high-frequency interference. This approach is consistent with previous research and has been found to be effective in reducing noise artifacts in EDA signals(15). Further, the processed data were normalized using min-max scaling to ensure that the data values fell within a specific range. In numerous studies, skin conductance (SC) has been widely used to measure EDA. The SC has two components: tonic and phasic. The tonic signal is an enduring baseline that is characterized by a gradual shift in the skin conductance level (SCL), which changes slowly, as well as other autonomous physiological activities(16). The phasic signal, or skin conductance response (SCR), is a rapid response caused by the presentation of external stimuli and experience of emotions. Separating these signals is essential for accurate measurements. The cvxEDA algorithm(4) was applied to decompose the EDA signal into tonic and phasic components, using standard parameter settings (γ = 0.01, α = 0.4, δ = 0.8). Only the phasic component, which represents rapid sympathetic fluctuations, was used for the feature extraction.

2.3.2. Feature extraction using discrete wavelet transform

This study utilized a discrete wavelet function to separate frequency components and their corresponding amplitudes from electrodermal activity (EDA) signals. The EDA signal was segmented into various subbands using a Discrete Wavelet Transform (DWT), each comprising different frequency components. As part of our EDA, we used the detailed coefficient obtained through the discrete wavelet transform (DWT)(14) as a feature. Wavelet analysis of a signal consists of translations ($k \in Z$) of the father wavelet $\phi(x)$ (scaling function), and dilation and translation ($k \varepsilon Z, j_0\ \varepsilon Z$) of the mother wavelet $\varphi\,(x)$. The wavelet representation of signal f(x) is

$$f(x) = \sum_k c_{j_0}(k), \emptyset_{j_0,k}(x) + \sum_{j=j_0} \sum_k d_{j,k}, \varphi_{j,k}(x) \tag{1}$$

In the DWT, the wavelet function serves as a type of frequency filter or refinement for signal processing, where $\phi(x)$ (low-pass) and $\varphi\ (x)$ (high-pass) filter the signal. The signal can be repeatedly decomposed into multiple levels using this procedure. All of these coefficients can accurately depict the complete traits of the original signal. With the help of the DWT, the EDA signal was segmented into various subbands, each comprising different frequency components. The EDA signal was decomposed into three levels using the Daubechies wavelet (DB4) (18) function with compact support and orthogonality. The Db4 wavelet base function was used because of its nearly optimal localization. Figure 2 illustrates the three-level wavelet decomposition of the EDA signal into approximate signals (A1-3 in the higher frequency bands) and details (D1-3 in the lower frequency bands). We used the rolling window technique on the phasic component of the EDA signal to compute the features with a step size of 50. Each rolling window's coefficient efficiently defines the characteristics of the signal. We extracted the entropy, different statistical features, root mean square value, zero crossing rate, and mean crossing rate features from each sub-band of the phasic component of the EDA signal for each window. Seventeen features were extracted 17 features. These features are utilized to take advantage of the nonlinear and nonstationary properties of the EDA. table 2 describes the experiment and extracts the feature summary.

Table 2. Experiment and extracted feature summary

Affect analysis	**Measured Signals**	**Extracted features**	
		Wavelet Features	**Time Frequency domain feature**
Neutral, Pleasant, Unpleasant	EDA (Sampling rate 15Hz)	Approximation and detail coefficient	entropy, median, mean, standard deviation, variance, 5th percentile value, 25th percentile value, 75th percentile value,95th percentile value, midhinge, trimean, root means square value, Area under curve, zero crossing rate, mean crossing rate, kurtosis, skewness

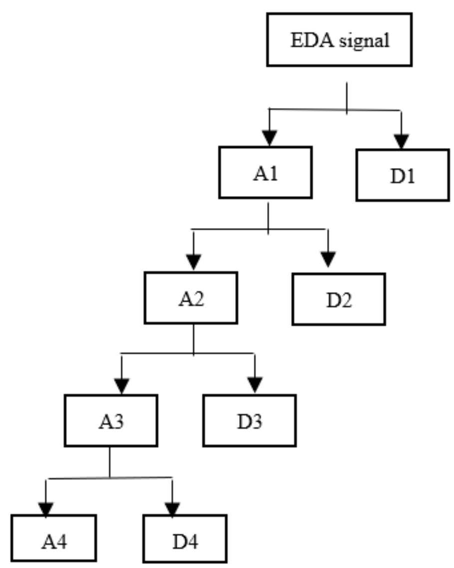

Fig 2. The schematic of three-level wavelet decomposition of EDA signal

2.3.3. Feature Selection

We used Shapley Additive Explanations (SHAP)[17] to objectively quantify feature importance and identify the most discriminative physiological features derived from EDA signals. We calculated SHAP values only on the training data using a Random Forest classifier to enhance robustness against multicollinearity. To validate the stability of our findings, we employed leave-one-subject-out cross-validation (LOSO-CV) exclusively on the training set of each LOSO-CV fold, ensuring generalizability across participants. Figure 3 illustrates the ranked feature importance derived from the SHAP analysis. The bars represent the mean absolute SHAP values for all participants.

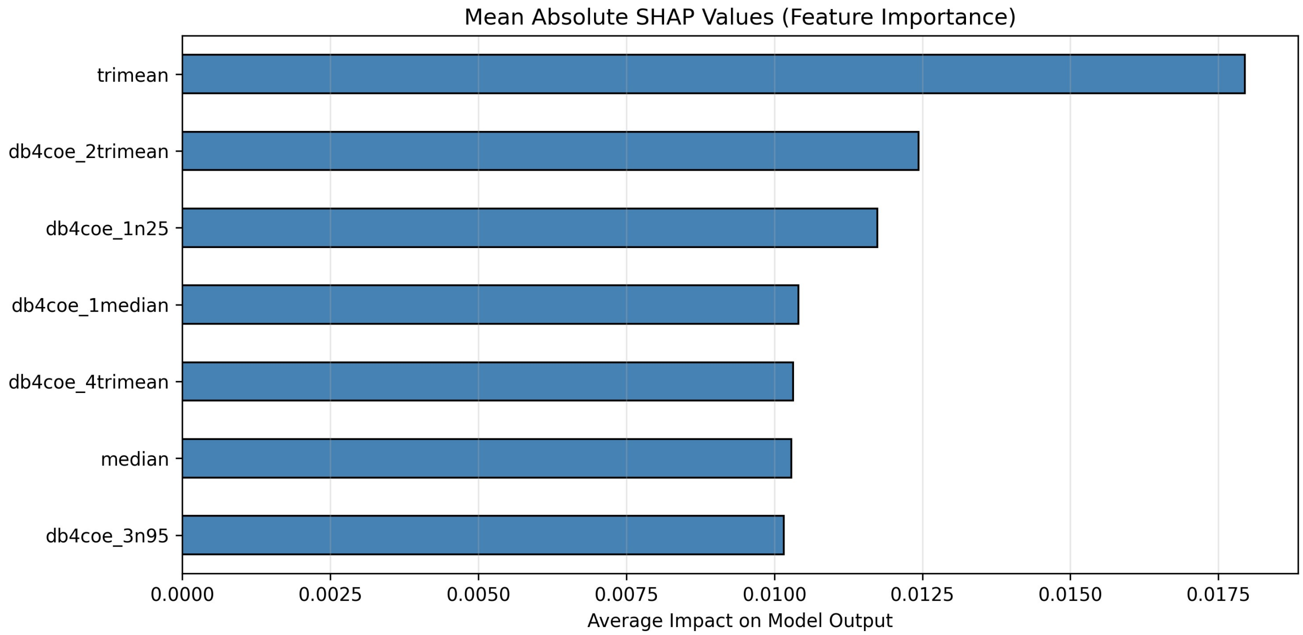

Fig 3. Ranked feature importance from SHAP analysis

2.3.4. MLP based emotion classification model

For classification, a multilayer perceptron (MLP) [18] was used to exemplify a neural network model meticulously constructed to find the optimal balance between representational capacity power and computational efficiency. The architecture design consisted of three hidden layers with 128, 64, and 32 neurons, enabling hierarchical feature extraction through consecutive nonlinear transformations. The layer-wise transformation employs rectified linear unit activation:

$$z^{(l)} = ReLU(\theta^{(l-1)}a^{(l-1)} + \beta^{(l)}) \tag{2}$$

We minimized cross-entropy loss with L2 regularization (λ=0.0001) and implemented a complete rotation validation strategy across all P=15 participants (LOSO-CV):

$$\emptyset = \frac{1}{15}\sum_{P=1}^{15}\delta\left(\overline{y}_P, y_P\right) \tag{3}$$

The validation procedure was cycled through LOSOCV where Training on P-1 participants and evaluation of the excluded participant rotated until all participants had served as validation cases. Adam updates with early stopping if the validation loss increases over 15 epochs. Figure 4 illustrates a schematic of the proposed approach.

3 Result and Discussion

This study evaluated a proposed feature extraction method for classifying emotions as neutral, pleasant, or unpleasant. Our primary objective was to analyze emotions using EDA signals. Research employing physiological signals for emotion analysis in minors remains scarce as most studies focus on adults (e.g., DEAP and PAFEW) or multimodal clinical settings [19]. Our study fills this gap by demonstrating that wavelet-processed EDA achieves **79.1**% accuracy, **0.79** macro-F1, and **0.79** balanced accuracy under LOSO-CV with 95% CIs of $\pm$3.4%. in classifying children's emotions in a naturalistic environment, a 5–6% improvement over prior multimodal pediatric studies (e.g., study (22)'s 74.96% accuracy with EDA, HRV, and facial cues). The narrow confidence bounds indicated consistent generalizations across the 15 subjects. This challenges the assumption that multimodal fusion is essential for reliable pediatric emotion recognition. Figure 5(a) shows the LV fold-wise accuracy of the different participants in the proposed study. Figure 5(b) shows the normalized confusion matrix for all the children using LOSO-CV. The true emotional class is shown in each row and the predicted class proportions are shown in each column. The diagonal

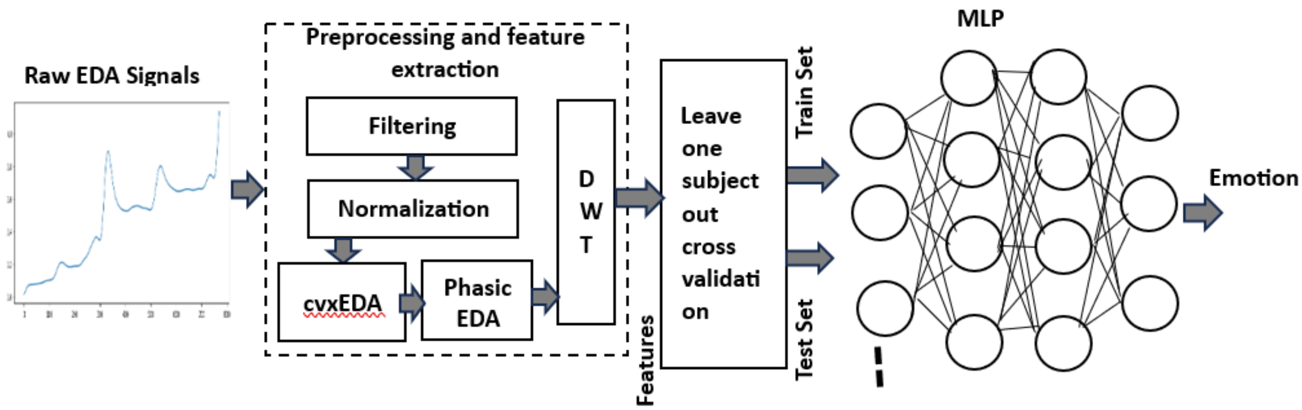

Fig 4. Schematic pipeline of proposed approach

values indicate the correct classification rate. Neutral emotions were correctly classified 73% of the time, positive emotions 79% of the time, and negative emotions 80% of the time.

Research [9] showed that wavelet features outperform conventional time-domain features in the application of child EDA. Our MLP classifier improved accuracy by 5% over their SVM, likely because of its ability to model complex, non-phasic EDA patterns (e.g., midhinge, trimean) that are prominent in children. The[20] Study's success with multimodal synchrony underscores the broader trend of fusing EDA with HRV for emotion recognition. However, our results demonstrate that wavelet-processed EDA alone can achieve a comparable accuracy for child-specific classification. A study[21] reported a 4–5% improvement in classification accuracy using deep learning for feature extraction and convolutional neural networks (CNNs) for arousal-valence detection in adults. This finding is consistent with our results. It is important to note that the data were obtained from the already available AMIGOS database.

Research[22] created a multimodal database for emotion analysis when adult participants engaged in face-to-face conversations alongside remote conversations, with self-reporting utilized for arousal and valence. However, unlike adult-centric studies (e.g., the DEAP dataset), our work focuses on children whose EDA signals exhibit higher inter-subject variability due to developmental factors and achieved an average F1-score of 80.33% for neutral, 80% for pleasant, and 79.90% for unpleasant emotions. Our use of time-frequency entropy, percentiles, and SHAP-based feature selection captured fine-grained patterns in the EDA signals. Our study also tackles class imbalance using the synthetic minority oversampling technique (SMOTE) and Gaussian noise augmentation with a standard deviation of 0.1. This approach enhanced the generalization of our model to unbalanced pediatric data, where neutral states accounted for only 23% of the sample. SHAP analysis identified the most significant features that contributed to distinguishing between unpleasant and pleasant states, which have not been emphasized in other studies. However, our approach utilized non-phasic trends, such as midhinge and trimean, along with wavelet features, to classify neutral states. This is an innovative contribution to the study of pediatric EDA. A limitation shared by[4] is its reliance on unimodal EDA, and future work should integrate multimodal validation (e.g., facial cues or other physiological signals PPG) to resolve ambiguities in emotional states and include a broader range of emotions. By leveraging wavelet-based feature engineering, developmentally aware modelling, and effective class imbalance mitigation, we set a benchmark for EDA-based emotion recognition in children, which is a crucial step toward fair affective computing.

4 Conclusion

The present study proposes a new method for emotion recognition using an emotibit sensor based on EDA signals collected from typically developing children. To conduct the experiment, a multimodal dataset was created from recordings of 15 children aged between 8 and 12 years. The EDA signal for this dataset is used in the proposed method. Wavelet transformation was used to provide a time-frequency analysis of the EDA signals. These extracted nonlinear features generate a reliable feature space for emotion recognition. The study used the Db4 wavelet function for feature extraction, SHAP for feature selection, and MLP for participant-wise classification. The empirical results suggest that the extracted features and the proposed approach exemplify the strong performance of our innovative methodology in achieving an 80% classification rate. Our approach has shown great potential for obtaining high accuracy in children's emotion classification tasks. The present study's emotional categorization is

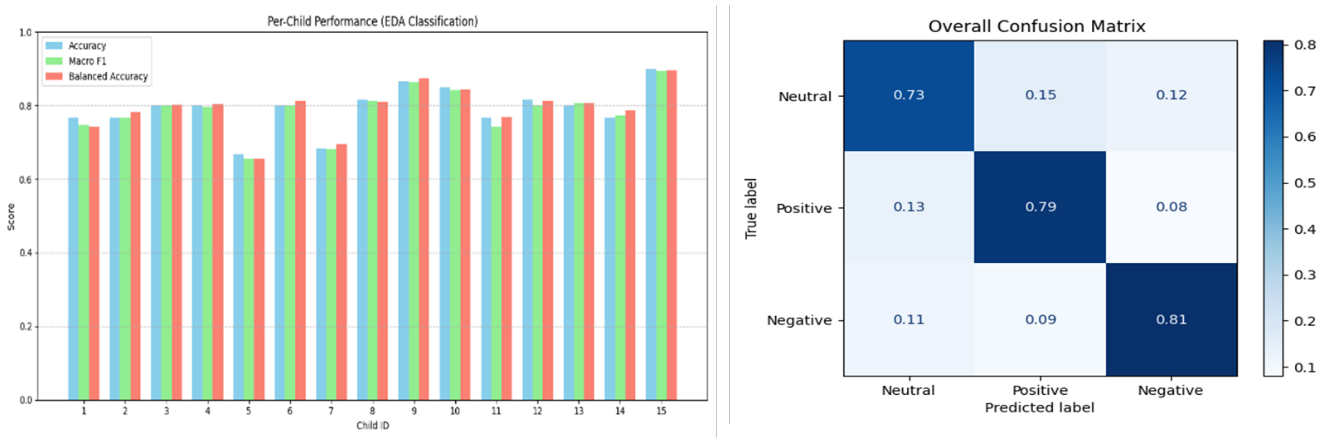

Fig 5. (a) LOSO-CV participant-wise accuracy. (b) Normalized confusion matrix across all children

constrained to three classes and is based solely on EDA data from limited children. This limitation poses a potential challenge for accurately capturing and classifying a broader range of emotions. In the future, we aim to better understand children's emotional experiences using multimodal data-fusion methodologies. It would be appropriate to incorporate an extensive range of emotions, specifically, disgust, sadness, excitement, and surprise. This approach will enable us to gain insight into children's emotional experiences, which has the potential to facilitate cognitive, social, and emotional development.

5 Author Contributions

Conceptualization, methodology, software, validation, formal analysis, investigation, resources, writing —original draft preparation, writing—review, and editing done by Kavita Choudhary under the supervision of Dr. Gend Lal Prajapati.

6 Data Availability

The dataset generated in the current study is available from the authors upon request.

7 Conflict of interest

The authors declare that they have no conflicts of interest.

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