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Implicit Measurement-Based ASD Dynamic Material Emotion Perception Assessment Method

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Abstract. As the basis of emotional communication and social interaction, emotional perception is a good indicator for the development of individual social skills. In this paper, a dual-modal emotion perception evaluation method based on electrical skin signal (EDA) and electrocardiogram signal (ECG) is proposed to provide more accurate intervention and treatment methods for children with autism (ASD), and at the same time propose the feasibility of multidimensional research on emotions from the physiological perspective. Methods Through the emotion perception experiment, the electrodermal signal and ECG signal of the subject were synchronously collected based on implicit measurement, the relevant features of the event were extracted, and the baseline correction, normalization and normality tests were carried out, and the dynamic material emotion perception evaluation dataset was formed together with the rehabilitation teacher evaluation score, and the ASD emotion perception evaluation model was constructed by the least squares method (OLS). Results Based on the SC_{Mean}, $Tonic_{Mean}$ features, SDNN, $Power_{Normalized}$, and SD2 features of electrodermal signals, the OLS linear regression perception evaluation model can realize the mapping of physiological indicators to emotional perception evaluation (coefficient of determination of electrodermal signal model R2=0.994; coefficient of determination of ECG signal model R2=0.970). At the same time, it also shows that OLS can combine the physiological indicators of electrodermal and ECG signals to better assess the emotional perception of ASD.

Keywords: children with autism; emotional perception; Dermatomy; ECG signals; OLS linear regression

1 Introduction

Autism is characterized by widespread neurodevelopmental disorders, which result in an inability to accurately perceive others' emotions during interactions and engage in normal social activities [1]. Emotion perception ability serves as the foundation for emotion communication and social relationships and is a good indicator of individual

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K. M. Salleh et al. (eds.), *Proceedings of the 2023 International Conference on Applied Psychology and Modern Education (ICAPME 2023)*, Advances in Social Science, Education and Humanities Research 803,
https://doi.org/10.2991/978-2-38476-158-6_22

development and social adaptation [2]. Assessing the emotion perception ability of children with autism and intervening in a tailored manner is one effective method to help them integrate into society.

Studies have shown that the emotion perception ability of children with autism follows a trajectory of delayed development and exhibits significant differences from typically developing children in perceiving six basic emotions. For example, Wallace et al. [3] using the Emotional Multi Morph Task, found that children with autism had significantly lower accuracy rates in recognizing the six basic emotions compared to typically developing children. Currently, the assessment tools used for children with autism primarily focus on the evaluation of their social adaptation abilities, such as the Psychoeducational Profile (PEP) and the Vineland Adaptive Behavior Scales (VABS) [4]. However, there is limited assessment specifically targeting emotion perception ability, and there is a lack of standardized behavioral assessments or specialized scales supporting the evaluation of emotion perception ability in children with autism [5]. Physiological signals are closely related to autonomic nervous system activity, and through feature extraction and data analysis, they can provide information regarding thoughts, emotions, and behaviors [6]. With the development of non-invasive data collection techniques [7], physiological signals are gradually being used in emotion research involving special populations [8].

Therefore, this study utilizes animated films as dynamic stimuli and combines implicit measurement techniques such as Electrodermal Activity (EDA) and Electrocardiogram (ECG) to explore the emotion perception ability of individuals with (ASD) towards dynamic materials. The aim is to construct an emotion perception assessment model for ASD and provide new theories and methods for intervention and treatment in ASD.

2 Design and Process of Emotion Perception Assessment Based on EDA and ECG

To accurately capture the underlying perception-evolution mechanisms of children with autism towards dynamic stimuli, this study utilizes implicit measurement techniques to extract relevant physiological indicators of ASD and emotional state changes. A dual-modal emotion perception assessment model is constructed using both electrodermal activity (EDA) and electrocardiogram (ECG) signals. The research process is illustrated in Figure 1 and is outlined as follows:

(1) Acquisition of emotion perception from dynamic stimuli based on implicit measurement: Experimental stimuli samples are constructed through literature analysis, questionnaire surveys, and other methods. The experimental samples are presented using the ErgoLAB Human-Machine Synchronization Platform by Jinfa Technology [9].

(2) Construction of the dynamic material emotion perception dataset: Synchronization of EDA and ECG data is performed using the ErgoLAB physiological wearable devices by Jinfa Technology [10]. The EDA skin conductance response [11] and HRV (heart rate variability) analysis module [12] in the ErgoLAB multimodal data analysis platform are used for data processing and feature extraction. The resulting features,

along with assessments by ASD rehabilitation teachers, form the emotion perception dataset.

(3) Construction of the dynamic material emotion perception assessment model based on linear regression: Using the emotion perception dataset, an emotion perception assessment model is built based on ordinary least squares (OLS) linear regression. This model establishes the mapping relationship between physiological signals and emotion perception, enabling the prediction of the emotion perception ability of individuals with ASD towards dynamic materials.

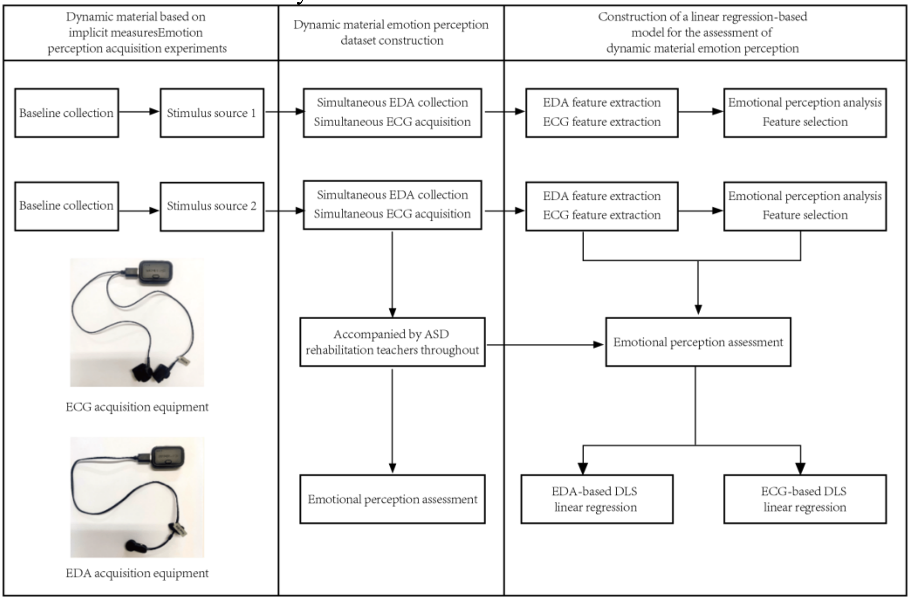


Fig. 1. Research Process Diagram

3 Emotion Perception Acquisition Experiment Based on Implicit Measurement of Dynamic Materials

3.1 Dynamic Experimental Materials

In this section, animated films are used as the target dynamic stimuli. Through literature analysis, questionnaire surveys, and communication with ASD rehabilitation teachers, the animated film segment "Pleasant Goat and Big Big Wolf: The Super Snail Adventure" is selected as the dynamic stimulus. The emotional types of the stimuli are divided into positive and negative categories (positive segments contain elements like pudding and candy, while negative segments depict the separation of Pleasant Goat from his parents).

3.2 Experimental Participants

With the support of Dongguan Rehabilitation School, three male participants with mild Autism Spectrum Disorder (ASD) are recruited for the experiment. Their ages are 12, 13, and 15 years old, respectively.

3.3 Experimental Procedure

During the experiment, the participants' electrodermal activity (EDA) and electrocardiogram (ECG) signals are collected simultaneously. Under the guidance of the teacher, the participants are familiarized with the experimental procedure and conduct the experiment under the teacher's supervision throughout. Considering the special characteristics of the participants, the baseline collection for the positive phase (calm state) is reduced to 60 seconds, and the baseline collection for the negative phase (calm state) is reduced to 30 seconds. After a sufficient rest period following the positive phase, the participants proceed to the subsequent experiment of the negative phase to ensure the comfort of the experiment. Meanwhile, the ASD rehabilitation teacher is present throughout the experiment, providing support and conducting assessments of the participants' states and emotional intensity (rated on a scale of 0-1). The experimental procedure is illustrated in Figure 2.

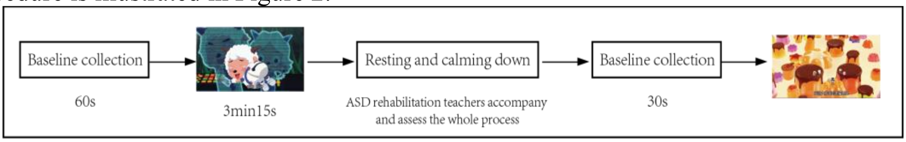
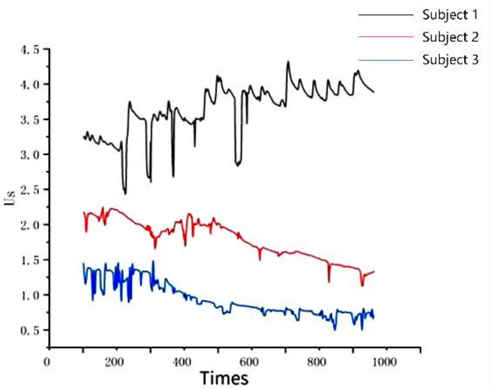


Fig. 2. Experimental Procedure

3.4 Experimental Data Analysis

3.4.1 Analysis of Electrodermal Activity (EDA) Signals.

The raw EDA signals obtained from the three participants in the experiment are shown in Figure 3. The acquired data is further processed with Gaussian smoothing to reduce noise.



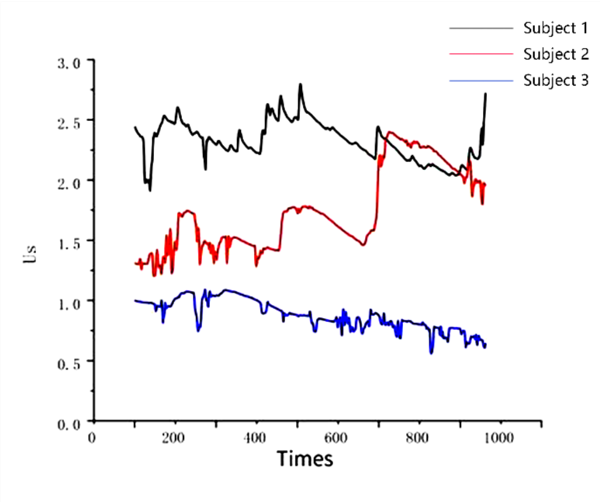


Fig. 3. Waveforms of Positive Segment (Left) and Negative Segment (Right)

The event-related Skin Conductance Response (ER-SCR) features are extracted, which are commonly used to measure the correlation between specific stimulus events and the level of emotional arousal [13]. Rise Time represents the average time for each SCR to rise, reflecting the individual's responsiveness to the stimulus, where a shorter time indicates a faster response to the stimulus. Amplitude Summary (Amp) represents the magnitude of the SCR response, with a larger amplitude indicating a stronger response to the stimulus [14]. The feature statistics of the positive segment and negative segment are shown in Table 1.

Table 1. ER-SCR Feature Statistics

Segment Type	ER-SCR		
	Count	Rise Time(s)	Amp(μs)
Positive	15	1.77	0.19
Negative	21.7	1.52	0.24

3.4.2 Analysis of Electrocardiogram (ECG) Signals.

The acquired ECG data from the experiment is subjected to wavelet denoising, and nonlinear analysis is performed using a scatter plot to extract the A++ and B-- indices [15]. A++ represents the points in the first quadrant, indicating an increase in consecutive heartbeat intervals and reflecting parasympathetic nervous system activity. A higher value indicates stronger activity. B-- represents the points in the third quadrant, indicating a decrease in consecutive heartbeat intervals and reflecting sympathetic nervous system activity. Again, a higher value indicates stronger activity. The scatter plots of the difference between consecutive heartbeat intervals for Participant 1 in the positive segment (left) and negative segment (right) are shown in Figure 4.

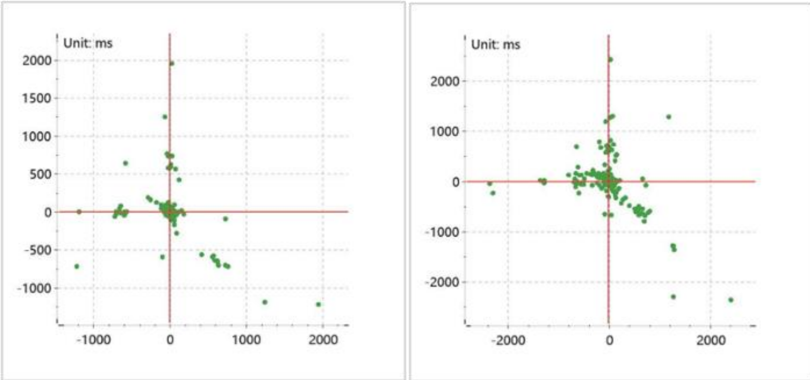


Fig. 4. Scatter Plots of Differences

To accurately study the relationship between electrocardiogram (ECG) signals and emotions, it is necessary to account for individual differences and variations in different states over time. In this experiment, individual normalization and baseline data correction were performed to remove individual differences. The calculation is performed as shown in Equation 1, where X_emotion represents the skin conductance data during the stimulus presentation, and X_calm represents the ECG data during the calm state (baseline).

$$X_0 = X_{emotion} — X_{calm} \tag{1}$$

After baseline data correction and averaging across participants, the feature statistics of the positive and negative segments are shown in Table 2.

Table 2. Feature Statistics of Difference Scatter Plots

Segment Type	A++	B--
Positive	19	12.7
Negative	35.33	29

3.4.3 Conclusion.

Based on the analysis of the skin conductance (SC) signal, it was found that the negative segment had a higher number of ER-SCRs and Amp (µs), and a lower Rise Time compared to the positive segment. In the analysis of the electrocardiogram (ECG) signal, it was observed that the negative segment had higher values of A++ and B-- compared to the positive segment. These findings suggest that the participants had a stronger perception of sad dynamic materials.

4 Construction of Dynamic Emotional Perception Dataset

Based on the analysis from the previous section, in this section, the physiological data from the negative segments, along with the ASD teacher's evaluation data, were used to construct the emotional perception dataset. A total of 8 data samples were obtained from the 3 participants, including 3 baseline data, 3 stimulus data, 1 average baseline data for each participant, and 1 average stimulus data for each participant.

The skin conductance (SC) signal was subjected to Gaussian smoothing and analyzed in the time domain to extract SC, Tonic Data, and Phasic Data indicators[16]. SC is related to sweat secretion and represents the activity level of the sympathetic nervous system[17]. Tonic Data is associated with the level of autonomous arousal, while Phasic Data is related to the level of emotional arousal[18].

The ECG signal was subjected to wavelet denoising and analyzed in the time domain, frequency domain, and nonlinear domain to extract SDNN, normalized LF power, SD2, and B-- indicators[19]. SDNN is a sensitive index for assessing sympathetic nervous system function[20]. LF power reflects the activation information of the sympathetic nervous system. SD2 represents long-term variability and has a strong correlation with sympathetic nervous system activity. B-- represents the third quadrant point, which indicates a decrease in consecutive heartbeats and an increase in heart rate, representing sympathetic nervous system activity. The ECG frequency domain analysis (power spectral density plot) and nonlinear analysis (Poincaré plot[21]) for participant 1 are shown in Figure 5.

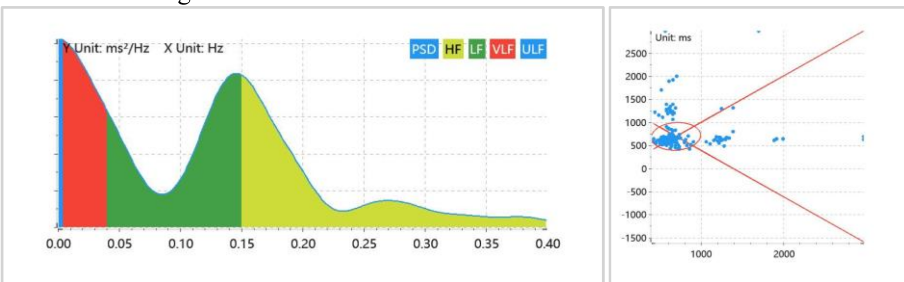


Fig. 5. Power Spectral Density Plot (Left) Poincaré Plot (Right)

5 Construction of the Emotion Perception Assessment Model for Dynamic Materials Based on Linear Regression

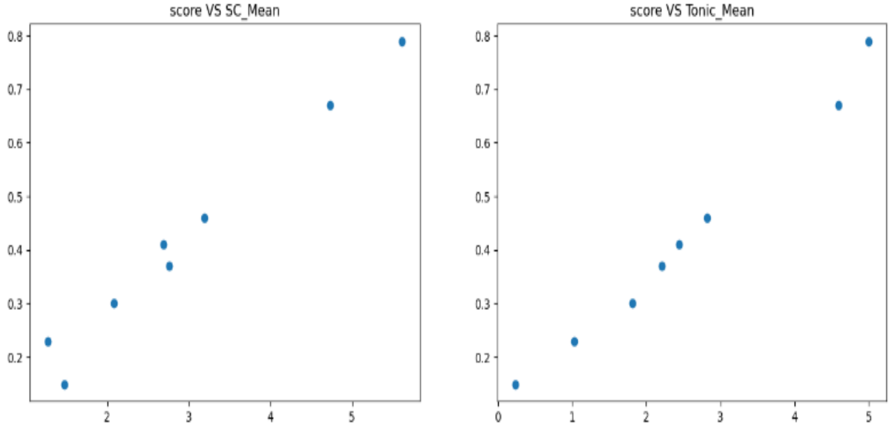
The main idea of Ordinary Least Squares (OLS) [22] is to determine unknown parameters (usually in the form of a parameter matrix) that minimize the sum of squared errors (also known as residuals) between the true values and predicted values. The formula for calculating OLS is shown in Equation 2, where y_i represents the true values and y_hat_i represents the corresponding predicted values. OLS can find the best function fit for the data by minimizing the sum of squared errors. In this study, OLS linear regression is applied to construct the emotion perception assessment model.

$$E = \sum_{i=0}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \tag{2}$$

5.1 OLS Linear Regression Based on Skin Conductance Level (SCL)

Before constructing the model, a normality test was conducted using the Shapiro-Wilk test in SPSSAU for SCMean, TonicMean, and PhasicMean. Since the sample size of the research data was all ≤50, the S-W test was used. PhasicMean ($p=0.035$) showed significant non-normality ($p<0.05$), indicating that PhasicMean does not follow a normal distribution. On the other hand, SCMean ($p=0.424$) and TonicMean ($p=0.706$) showed no significant non-normality ($p>0.05$), indicating that SCMean and TonicMean exhibit normality. Therefore, the PhasicMean indicator was excluded.

After the normality test, a correlation analysis was performed between SCMean, TonicMean, and the ASD teacher assessment scores. The Pearson correlation coefficient between SCMean and the ASD teacher assessment scores was 0.97801, while the Pearson correlation coefficient between TonicMean and the ASD teacher assessment scores was 0.98043. Based on these indicators, an OLS linear regression model was established, resulting in a binary linear regression equation: score = 0.0563 × SCMean + 0.0804 × TonicMean + 0.0526. The coefficient of determination (R2) was 0.994. The scatter plot of the original data and the comparison between the actual scores and predicted scores are shown in Figure 6. The predicted results demonstrate that the predicted values follow the same trend as the actual values, and the differences between some predicted and actual values are small. This indicates that the OLS linear regression model can map physiological indicators to emotion perception assessments.



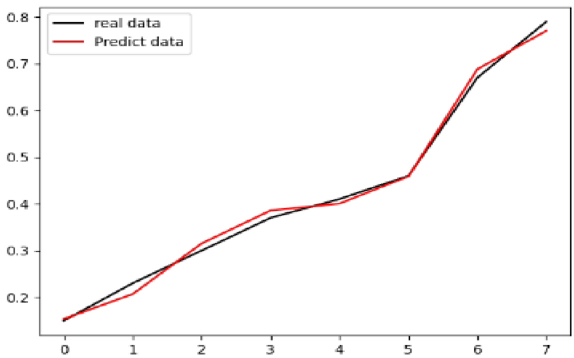
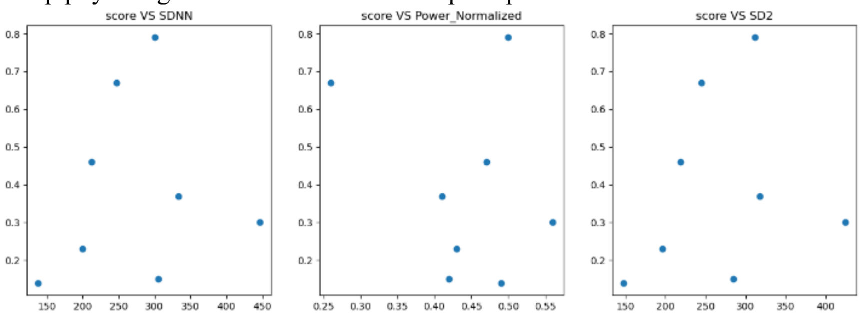


Fig. 6. Scatter plot of the original data and OLS linear regression prediction results (1)

5.2 OLS Linear Regression Based on ECG

For SDNN, PowerNormalized, SD2, and B--, a normality test was conducted using SPSSAU. Since the sample size of the data was ≤50, the Shapiro-Wilk test was used. B-- showed significance with $p=0.046$ ($p<0.05$), indicating that B-- does not follow a normal distribution. On the other hand, SDNN ($p=0.901$), PowerNormalized ($p=0.382$), and SD2 ($p=0.924$) did not show significance ($p>0.05$), indicating that SDNN, PowerNormalized, and SD2 have a normal distribution. Therefore, the B-- indicator was excluded.

After the normality test, a correlation analysis was performed between SDNN, PowerNormalized, SD2, and ASD teacher assessment scores (score). The Pearson correlation coefficient between SDNN and ASD teacher assessment scores was 0.12688. The Pearson correlation coefficient between PowerNormalized and ASD teacher assessment scores was -0.27405. The Pearson correlation coefficient between SD2 and ASD teacher assessment scores was 0.20723. Based on these indicators, an OLS linear regression model was established, resulting in a three-variable linear regression equation: Score = -0.0220×SDNN - 1.8275×PowerNormalized + 0.0254×SD2 + 0.3794. The coefficient of determination (R2) was 0.970. Figure 7 shows the scatter plot of the original data and the test results. The prediction results indicate that the predicted values have a similar trend to the actual values, and the differences between some predicted values and actual values are small. This suggests that the OLS linear regression model can map physiological indicators to emotion perception assessment.



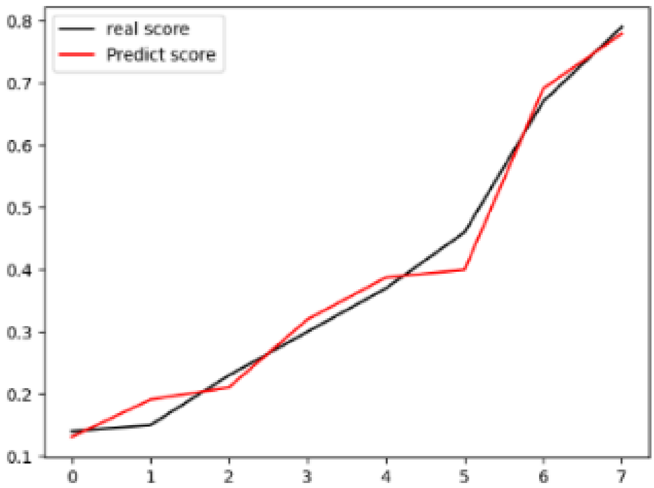


Fig. 7. Scatter plot of the original data and OLS linear regression prediction results (2)

6 Conclusion

To achieve more accurate and objective assessment of emotion perception in individuals with Autism Spectrum Disorder (ASD), this paper proposes an evaluation method based on implicit measures and OLS linear regression. By synchronously collecting skin conductance and electrocardiogram signals through implicit measurement techniques, objective data of ASD individuals were obtained, revealing their stronger perception of negative emotions. Additionally, in conjunction with ASD teacher evaluations, a dynamic material emotion perception assessment dataset was constructed. By using OLS linear regression, an emotion perception evaluation model based on dynamic materials was established. Experimental results demonstrate that the proposed method can effectively assess the emotion perception of individuals with ASD. Furthermore, this method provides a theoretical basis and experimental evidence for assisting in the intervention and treatment of children with autism. It also validates and highlights the feasibility and importance of physiological emotion measurement in multidimensional emotion research and exploring the internal mechanisms of emotions.

Acknowledgements

The work in this paper was supported by the Ministry of Education Humanities and Social Sciences Research Youth Fund Project: Research on Product Design Strategy for Children with Autism Based on Emotion Measurement Theory (project approval number: 21YJCZH184).

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