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Computerized Analysis of Face Emotion Recognition Skills and Facial Behaviors in Children with Attention Deficit Hyperactivity Disorder

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Children with attention deficit hyperactivity disorder (ADHD) often show impairments in social cognition and emotion recognition, especially in facial expressions, tone of voice, and body posture.*
- *These deficits are related to difficulties in empathy, peer relationships, and long-term prognosis.*
- *Prior research has reported inconsistent findings: some studies confirm significant emotion recognition deficits, while others find no difference compared to controls.*
- *Nonverbal behaviors, such as facial expressions, are crucial in clinical assessments, but traditional methods are subjective.*

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ABSTRACT

Objective: The aim of this study was to investigate the facial expressions of children diagnosed with attention deficit hyperactivity disorder (ADHD) using computerized facial analysis and to examine their emotion recognition abilities.

Methods: A total of 56 children with ADHD and 45 control subjects aged 6-12 years were included. The Diagnostic Analysis of Nonverbal Expressions-2 (DANVA) was used to measure the participants' emotion recognition abilities. One group of participants watched animated film scenes lasting an average of 7 minutes, and their facial behaviors were recorded on video. OpenFace software was used for video analysis. Support Vector Machines (SVM), naive Bayes, and logistic regression machine learning methods were used to distinguish between the data of the ADHD and control groups.

Results: The significant difference found in DANVA total scores indicating poorer emotion recognition skills in ADHD was not significant when intelligence levels were controlled. Children with inattention as the primary symptom made significantly more errors in emotion recognition from posture and total scores in DANVA child faces and overall compared to the other groups. According to computerized facial analysis, Video 1, which predominantly featured fear and anger emotions, was the most distinctive video for both healthy controls and the ADHD group. When analyzing AU units, AU12 (lip corner pulling), AU07 (eyelid raising), AU09 (nose wrinkling), AU45 (eye blinking), and AU06 (cheek raising) were the most distinctive features.

Conclusion: Emotion recognition levels differed among ADHD cases according to clinical subtypes and comorbid psychiatric disorders. The most significant difference between the ADHD and control groups during emotion-containing video viewing was observed while watching sad videos. The findings of this study can be considered promising for the diagnostic validity of machine learning methods in ADHD, one of the most common neurodevelopmental disorders.

Keywords: Attention deficit hyperactivity disorder, emotion recognition, face emotion recognition, facial movements, OpenFace

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WHAT DOES THIS STUDY ADD TO THIS TOPIC?

- *This is the first study to combine computerized facial analysis with standardized emotion recognition tests (DANVA) in children with ADHD.*
- *It shows that inattentive subtype children have more pronounced emotion recognition deficits, particularly in recognizing child faces and postures.*
- *The study identifies specific facial action units (AU12, AU07, AU09, AU45, AU06) as discriminative markers between ADHD and controls.*
- *Findings highlight that sadness-related videos are the most sensitive stimuli to differentiate ADHD from controls.*
- *Results support the potential of machine learning–based facial behavior analysis as an objective diagnostic tool in ADHD.*

INTRODUCTION

Attention deficit hyperactivity disorder (ADHD) is a neurodevelopmental and psychiatric disorder characterized by symptoms of inattention, hyperactivity, and impulsivity. In previous studies with children and adolescents diagnosed with ADHD, cold executive functions have been studied much more extensively. In recent years, interest in impairments in warm executive functions in ADHD has begun to grow. Evidence suggests that individuals with ADHD experience impaired emotion recognition, which is a key warm executive function, resulting in significantly greater difficulty interpreting emotional cues from facial expressions, tone of voice, and body posture compared to those without the disorder.[1]

Research on social skill deficits and social cognition in children with ADHD has increased in recent years. However, there are still very few studies on emotion recognition skills, which are part of social cognition. In our previous study,[2] children with Specific Learning Disorder (SLD) and control subjects were examined using OpenFace software. In that study, children watched 5-minute animated film scenes. Machine learning (ML) methods were subjected to 10-fold cross-validation analysis separately. The results demonstrated that computerized facial behavior recognition in children may assist in psychiatric assessment of SLI and other neurodevelopmental disorders. These findings suggest that, in the future, evaluating objective facial behavior may provide additional insights alongside traditional methods in neurodevelopmental disorders.

Recent neuropsychological research underscores that the challenges faced by children and adolescents with ADHD extend beyond the core symptoms of inattention, hyperactivity, and impulsivity, significantly affecting social cognition. A critical component of this impairment is Facial Emotion Recognition (FER), which serves as a gateway to successful social interaction. Studies have increasingly suggested that FER deficits in ADHD are not isolated incidents but are intricately linked to Executive Function profiles.[3] Specifically, deficits in inhibitory control and working memory common in ADHD may hinder the ability to process complex facial cues and rapidly changing emotional expressions.[4]

The importance of examining nonverbal communication, including body language, facial expressions, and tone of voice, in clinical practice has been recognized for many years. However, these examination findings can be subjective. There is still a need for valid, reliable, and objective assessment methods. Despite the recent increase in digital technology and machine learning methods, studies in this field are still in their infancy. In the near future, computer-assisted psychometric assessments, including computerized analysis of facial expressions, may become more widely used. This study aims to objectively evaluate facial movements as nonverbal behaviors. In this study, the emotion recognition levels of cases diagnosed with ADHD were examined, and computerized analysis of facial behaviors was performed.

MATERIAL AND METHODS

Participants

A group of 56 patients aged 6-12 years with a diagnosis of ADHD who visited our clinic, and a group of 45 healthy control subjects matched for age and gender, were included in the study. The patient group consisted of cases who were diagnosed with ADHD for the first time or who had a previous diagnosis of ADHD and had not used any medication in the last 3 months. Autism spectrum disorder (ASD), psychotic or bipolar disorder, anxiety disorders, substance use disorders, visual or hearing loss, known neurological disorders, or acute or chronic medical conditions that could alter neuropsychological test performance are exclusion criteria. The control group consists of individuals aged 6-12 years who visited a psychiatry or pediatrics outpatient clinic and reported no psychiatric or chronic medical illnesses. Control subjects were screened to ensure they reported no psychiatric symptoms or medical illnesses and met no DSM-5 criteria during the initial clinical and semi-structured interview.

Study Design

Cases aged 6-12 years who were referred to the outpatient clinic with their families, diagnosed with ADHD according to DSM-5 diagnostic criteria, met the inclusion criteria, and did not meet the exclusion criteria were directed to the researcher. Participants were informed about the study, and informed consent was obtained. During the initial interview with the participants and their mothers, a sociodemographic and clinical data form prepared by the researcher was completed. The K-SADS-PL was administered during the same interview. Subsequently, mothers were asked to complete the Brief Symptom Inventory (BSI) for themselves and the DSM-IV–based Screening and Assessment Scale for Attention Deficit and Disruptive Disorders (ADHD SCALES) and the Social Responsiveness Scale (SRS) for their children. While the mothers were completing the forms, the researcher administered the Diagnostic Analysis of Nonverbal Accuracy (DANVA) to the children via computer. Considering the exhausting effect of the forms and tests, a second appointment was given to the participants. Additionally, the child's teacher was asked to complete the ADHD SCALES and SRS forms and submit them to the researcher.

During this second appointment, computerized facial analysis was performed on the child. The participating children were shown three video clips, each lasting 2-3 minutes, and their faces were recorded with a 1200 × 800 resolution HD Nikon camera during the video presentations. These recordings were then analyzed using the OpenFace method. During the second appointment, the missing forms were completed.

Tests and Scales Used

Study Information Form: The study data form was prepared for this study to collect information about participants' age, family and developmental history, pregnancy and birth process, and medical problems.

Schedule for Affective Disorders and Schizophrenia for School-Age Children—Present and Lifetime Version: Schedule for Affective Disorders and Schizophrenia for School-Age Children-Present and Lifetime version (K-SADS-PL) is a semi-structured psychiatric interview method developed according to the DSM-IV psychiatric classification to determine the presence of common psychiatric disorders in childhood.[5] The Turkish validity and reliability study was conducted by Gökler and colleagues in 2004.[5] The K-SADS-PL is administered through interviews with both the mother/father and the child.

Turgay DSM-IV–Based Screening and Assessment Scale for Destructive Behavior Disorders: Developed based on DSM-IV criteria for ADHD, oppositional defiant disorder (ODD), and Conduct Disorder (CD). It includes nine items assessing attention deficit, six items assessing hyperactivity, 3 items assessing impulsivity, 8 items assessing ODD, and 15 items assessing DB. All items are scored on a 0-3 scale. The Turkish adaptation was conducted by Ercan et al.[6]

Social Responsiveness Scale: The SRS consists of 39 items that investigate observable socially relevant actions; 6 items that investigate whether language is used appropriately in social contexts; and 20 items that screen for symptoms directly related to autism.[7] A high total score indicates an increased level of social skill impairment. In the SRS, scores of 60-80 indicate mild to moderate impairment in social reciprocity, while scores above 80 indicate more severe impairment.[8] The Turkish version of the SRS was administered by Ünal and colleagues, and its internal consistency and test-retest reliability were found to be adequate.[9]

Brief Symptom Inventory: The BSI consists of 53 items. The BSI is a self-report scale with a 5-point Likert scale. Participants are asked to select the option that best describes their response for each item on the scale from "Never," "Somewhat," "Moderately," "Quite a bit," and "Very much," and scores are calculated on a scale of 0 to 4. Studies conducted on a Turkish sample have reported that the scale consists of five factors: "anxiety," "depression," "negative self-image," "somatization," and "hostility."[10]

Wechsler Intelligence Scale for Children-Revised: The WISC-R is the most commonly used measure for assessing the intellectual abilities of children aged 6-16 years. It has been standardized in Turkey.[11] The WISC-R test yields a total intelligence score and two main subscores (verbal and performance).

Diagnostic Analysis of Nonverbal Accuracy: Developed by Nowicki and Duke, DANVA is widely used in the assessment of nonverbal social processing skills.[12, 13]DANVA consists of 3 subtests: Children's Facial Expressions (DANVA-CE), Adult Facial Expressions (DANVA-AE), and Postures. Both the CF and AF contain 48 expressions, with 12 low-intensity and 12 high-intensity images. Additionally, 16 posture expressions are included, bringing the total number of expressions in the test to 64. All parameters were applied in this study. Four basic emotions were presented in these tests: happy, sad, angry, and fearful. Each response is coded as correct or incorrect. Scores are determined by counting the number of correct responses. DANVA has been found to have good internal consistency, test-retest reliability, and validity.[13]

Participants were shown 3 video clips, each lasting 2-3 minutes.

• Video 1: Scenes from The Lion King containing fear and anger.

• Video 2: Scenes from Tom and Jerry containing humor and comedy.

• Video 3: A scene from Bambi containing sadness.

During video presentations, patients' faces were recorded with a Nikon HD camera with a resolution of 1200x800. The OpenFace method was used to analyze participants' facial expressions.[14] Facial Action uUits (AU) obtained from video recordings can be analyzed using the OpenFace program. The OpenFace method predicts real-time facial AU density. The detection system uses appearance geometric features. Statistical analysis was performed using average values for each unit. The necessary permissions for using OpenFace have been obtained. The validity of the OpenFace method was aimed to be achieved by using the 9 highest-scoring AU subunits.

Data Analysis

Based on the power analysis we conducted using the study,[15] the minimum number of participants required for each group was calculated as 12, with 95% power using the Minitab 17.0 program. Due to concerns that insufficient data may be collected in some analyses and that missing data may occur, and to facilitate separate analysis of ADHD subgroups and comorbid groups, both the ADHD and control groups were formed with approximately 48 cases (12 × 4 = 48).

Data analysis was performed using SPSS (Statistical Package for Social Sciences) for Windows 21.0 (SPSS Inc, Chicago, IL). The normality of variable distributions was assessed using visual (histograms and probability plots) and analytical methods. In cases where normal distribution was observed, *t*-tests and Fisher's exact tests were used. In cases where normal distribution was not observed, Mann–Whitney *U* test, Quade ANCOVA, and Kruskal–Wallis tests were applied. In post-hoc analyses, Bonferroni correction was used when necessary. Relationships between variables were analyzed using Pearson or Spearman correlation tests. The level of statistical significance was set at $P < .050$.

Due to the multidimensional nature and multifactorial etiology of neurodevelopmental disorders, artificial intelligence and ML have gained increasing attention in this field in recent years. Among ML methods, the most commonly used ones include *support* vector machines, *decision trees*, and *deep learning* methods. When creating models, researchers using ML typically divide the data into training and test sets. The training set teaches the model, and the model's performance is evaluated based on how well it recognizes the test set. Researchers randomly divide the data using *cross-validation* methods. The model utilized automatically optimized machine learning algorithms with 10-fold cross-validation to ensure the robustness of the area under curve (AUC) results.[16]

In this study, *Machine* Learning methods were applied to the data (e.g., advanced analysis of facial expressions). The regression and classification coefficients of the AUs obtained every 0.3 seconds from Video 1, Video 2, and Video 3 were calculated, and the average values were recorded for each participant in the patient and control groups. RapidMiner Studio Academic software[17] was used for data analysis and modeling. Eight automatically optimized machine learning algorithms were used to classify the control and ADHD groups (*Naive Bayes*, *Linear Regression*, *Fast Large Margin*, *Deep Learning*, *Decision Trees*, *Random Forest*, *Gradient Boosted Trees*, *Support Vector Machines)*. All subsets and averages obtained from this process were calculated using 10-fold cross-validation for receptive operation characteristics (ROC) curves and AUC.

The classification of facial behavior data was performed using a multilayer feed-forward artificial neural network implemented within the H2O.ai framework. The model utilized a fully connected architecture, employing the Rectifier (ReLU) activation function in the hidden layers to effectively capture non-linear patterns while maintaining computational efficiency. To minimize the loss function and optimize convergence speed, the model was trained using Stochastic Gradient Descent (SGD) with an ADADELTA adaptive learning rate. To ensure robustness and prevent overfitting, the architecture incorporated *L1* and *L2* regularization along with Dropout techniques, enhancing the model's generalizability across ADHD and control samples. Model performance and diagnostic validity were evaluated via 10-fold cross-validation, with results quantified through ROC curves and AUC values to determine the discriminative power of the specific AU.

Ethical Approval

This research was deemed ethically acceptable by the Ondokuz Mayis University Clinical Research Ethics Committee, dated 16 December 2019, No. B.30.2.ODM.0.20.08/1844-56-992 and decision No. 2018/386. Written consent was obtained from the participants' parents, and verbal consent was obtained from the children themselves. All expenses related to the study were covered by the researcher.

RESULTS

The basic characteristics of the cases are presented in Table 1. The age and education levels of mothers and fathers were significantly lower in the ADHD group compared to the control group. As expected, household income was also significantly higher in the control group, where parental education levels were higher.

The two groups showed similar findings in terms of developmental parameters. Both maternal and paternal age at birth were significantly lower in the ADHD group ($P < .001$). In terms of sociodemographic data, a significant difference was found between the groups in household income ($P < .001$).

The SRS, one of the scales used to assess social cognition in cases, was completed by families and teachers. The SRS total score, which indicates impairment in social cognition as the score increases, was found to be statistically significantly higher in ADHD cases according to both the forms completed by families and teachers ($P = .001$). To control for the confounding effect of intelligence on social cognition, the WISC-R total score was controlled using the ANCOVA method, and the significant difference between groups in the SRS total score was maintained (Family; $F = 6.295$, $P = .014$) (Teacher; $F = 5.004$, $P = .029$). When the SRS total score is above 60, social responsiveness can be considered impaired. When scores are divided into two groups in this manner, a significantly higher rate of social impairment is observed in the ADHD group (Table 2).

The ADHD SCALES inattention score showed a very high correlation with all WISC-R sub-scores, DANVA-Child Face, and total and SRS scores. On the other hand, ADHD SCALES hyperactivity/impulsivity

Table 1. Comparison of the Basic Characteristics of the Groups

		ADHD (n = 56)	Control (n = 45)	Statistics	*P*
Age (months)		103.1 ± 16	104.1 ± 17	T: −0.386	.700
Gender	Male	85.7% (n = 48)	77.8% (n = 35)	χ^2: 0.219	.300
	Female	14.3% (n = 8)	22.2% (n = 10)		
Dominant Hand	Left	12.7% (n = 7)	11.6% (n = 5)	χ^2: 0.027	.869
	Right	87.3% (n = 48)	88.4 (n = 38)		
BMI		17.29 ± 2.6	17.84 ± 3.0	T: −0.897	.372
Mother's age		35.2 ± 4.8	39.3 ± 4.3	−T: 4,366	.001
Father's age		38.0± 4.3	42.6 ± 5.6	T: −4,640	.001
Mother's education level	Primary/middle school	53.6% (n = 30)	14.0% (n = 6)	χ^2: 20,87	.001
	High school	23.2 (n = 13)	20.9% (n = 9)		
	University	23.2% (n = 13)	65.1% (n = 28)		
Father's education level	Primary/middle school	46.4% (n = 26)	11.6% (n = 5)	χ^2: 26,255	0.001
	High school	30.4% (n = 17)	14.0% (n = 6)		
	University	23.2% (n = 13)	74.4 (n = 32)		
Household income (TL/month)		4055 ± 2797	7575 ± 3990	T: −5,054	.001

$^*P < .050$

ADHD, attention deficit hyperactivity disorder; BMI, body mass index; *T*, Student's *t*-test; χ^2, chi-square test.

Table 2. Comparison of Family and Teacher Social Reciprocity Scores

		ADHD (n = 56)	Control (n = 45)	Statistics	*P*
SRS parent version-total score		54.3 ± 18.3	36.2 ± 13.4	T: 5.290	.001*
SRS parent version	No impairment	63.5% (n = 33)	96.7% (n = 29)	χ^2: 77.817	.001*
	Impairment present	36.5% (n = 19)	3.3% (n = 1)		
SRS teacher version-total Score		58.8 ± 28.6	23.7 ± 11.2	T: 7.091	.001*
SRS teacher version	No deterioration	63.4% (n = 26)	100.0% (n = 27)	χ^2: 12.674	.001*
	Impairment present	37.6% (n = 15)	0.0 (n = 0)		

*$P < .05$.
ADHD, attention deficit hyperactivity disorder; SRS, Social Responsiveness Scale; T, Student's *t*-test; χ^2, Fisher's exact test.

scores were found to have statistically significant correlations with WISC-R verbal and total scores, DANVA-Adult Face and total scores, ANNE-BSI, and SRS scores. ADHD SCALES opposition/defiance scores have a significant correlation with WISC-R total and Mother-SRS scores. ADHD SCALES conduct disorder scores have a significant correlation only with Mother SRS scores (Table 3).

DANVA results revealed significant findings against ADHD in terms of total correct responses. When Bonferroni correction was not considered, this difference was found to stem primarily from significant differences in correctly identifying low-intensity adult facial expressions, postures, and fearful facial expressions (Table 4). On the other hand, SRS scores remained significant even when WISC-R total scores were controlled, while the significant difference observed in DANVA scores lost its significance when WISC-R total scores were controlled (Table 4).

Attention Deficit Hyperactivity Disorder and Computerized Facial Analysis

As mentioned in the Materials and Methods section, 8 automatically optimized ML algorithms were used to classify the control and ADHD groups. The ML algorithm with the highest AUC was selected for the results. The algorithm that demonstrated the best performance using only AUs was the Deep Learning method, and the top 5 variables selected by this algorithm with the highest weights are shown in Table 5. According to this analysis, video 1 can be considered the most discriminative video for both the healthy controls and the ADHD group. On the other hand, AU12 (lip corner puller), AU07 (eyelid stretcher), AU09 (nose wrinkle), AU45 (eye blink), and AU06 (cheek lifter) were the most discriminative features.

When these features obtained from Video 1 were compared between the ADHD and control groups, it was observed that the control group used AU12 at a statistically significant level more frequently. Table 6 shows the AU comparisons between the ADHD and control groups in Video 1.

Significant correlations were observed between specific facial Action Units (AUs) and emotion recognition abilities. A positive correlation was found between AU09 (Nose Wrinkler) and SRS scores ($r = 0.615$, $P = .002$), indicating that stronger activation of this unit was associated with higher levels of social responsiveness

Table 3. Correlation Between Scales

		1	2	3	4	5	6	7	8	9	10	11	12
ADHD scale	Inattention (1)												
	Hyperactivity(2)	0.682**											
	Opposition (3)	0.581**	0.795**										
	Conduct problems (4)	0.477**	0.671**	0.716**									
WISC-R	Verbal (5)	−0.574**	−0.371**	−0.324**	−0.163								
	Performance (6)	−0.326**	−0.172	−0.091	−0.072	0.629**							
	Total (7)	−0.488**	−0.281**	−0.217*	−0.118	0.887**	0.898**						
DANVA	Child face (8)	−0.240*	0.145	−0.065	−0.052	0.241*	0.153	0.230*					
	Adult face (9)	−0.189	−0.213*	−0.097	−0.092	0.346**	0.188	0.275**	0.306**				
	Adult posture (10)	−0.198	0.062	−0.156	−0.184	0.174	0.171	0.180	0.072	0.195			
	Total (11)	−0.384**	−0.251*	−0.178	−0.183	0.386**	0.245*	0.344**	0.689**	0.702**	0.567**		
Mother-BSI (12)		0.204	0.261*	0.176	0.051	−0.167	−0.189	−0.188	0.005	−0.105	0.056	−0.032	
Mother-SRS (13)		0.563**	0.406**	0.359**	0.243*	−0.438**	−0.332**	−0.411**	−0.135	−0.171	−0.030	−0.192	0.365**

Spearman correlation was performed.
*$P < .05$.
**$P < .01$.
BSI, Brief Symptom Invantory; DANVA, Diagnostic Analysis of Nonverbal Accuracy; SRS, Social Responsiveness Scale; WISC-R, Wechsler Intelligence Scale for Children-Revise.

Table 4. Comparison of DANVA Correct Answer Scores

		ADHD (n = 56) Median (Q1-Q3)	Control (n = 45) Median (Q1-Q3)	Statistics	*P* ANCOVA
Child face	High intensity (12 questions)	9 (8-10)	9 (9-10)	Z: −1.470	.142
	Low intensity (12 questions)	10 (9-11)	10 (9-11)	Z: −0.640	.522
	Total	19 (17-20)	19 (18-21)	Z: −1.288	.198
Adult face	Low intensity (12 questions)	8 (6-9)	8 (7-9)	Z: −2.066	.039* F:1.219 0.273
	High intensity (12 questions)	10 (8-11)	10 (10-11)	Z: −1.885	.059
	Total	18 (14-19)	19 (17-20)	Z: −2.293	.022* F:2.473 0.120
Posture (16 questions)		9 (7-10)	9 (8-11)	Z: −1.983	.047* F:0.065 0.800
Total (64 questions)		45 (40-47)	47 (45-50)	Z: −3.071	.002* F:1.639 0.204
		Mean ± SD	Mean ± SD		
"Fearful" correct number		10.88 ± 2.2	11.76 ± 1.6	T: −2.133	.036* F:0.222 0.639
"Angry" correct count		8.94 ± 2.2	9.79 ± 2.7	T: −1.608	.112
"Sad" correct count		12.33 ± 2.4	13.15 ± 2.2	T: −1.573	.120
"Happy" correct count		14.08 ± 1.7	14.44 ± 1.4	T: −1.044	.299

[a]*P* value determined by controlling the WISC-R total score in ANCOVA.
*$P < .05$: low intensity, high intensity.
ADHD, attention deficit hyperactivity disorder; F, ANCOVA; Z, Mann–Whitney *U*-test.

difficulties. Similarly, AU07 (Lid Tightener) correlated positively with child-face emotion recognition performance ($r = 0.497$, $P = .019$). In contrast, AU45 (Blink) exhibited a negative correlation with posture recognition performance ($r = -0.471$, $P = .027$), suggesting that increased blinking frequency may relate to weaker nonverbal posture interpretation. No other significant relationships were detected ($P > .05$).

DISCUSSION

Although the number of studies examining emotion recognition skills in ADHD cases has increased recently, according to a literature review, this study is the first to use computerized facial analysis in addition to emotion recognition skills, which are the most basic components of social cognition in ADHD.[18]

Children in the ADHD (mean = 103 months) and control (mean = 104 months) groups had a very similar mean age. Approximately four-fifths of all participants were male children, and a similar gender distribution is observed in clinical studies of ADHD.[19]It is a frequently reported finding in the literature that individuals with ADHD and their parents tend to have lower educational levels and, consequently, lower income levels.[20] In this study, it was found that the maternal age at birth was significantly lower in the ADHD group. The groups' pregnancy and birth histories, need for neonatal care, gestational age, and birth weight were similar.

In this study, approximately 70% of ADHD cases were accompanied by at least one psychiatric disorder. Comorbid diagnoses such as anxiety disorders, mood disorders, and autism spectrum disorders, which could potentially influence the study's core data, were excluded. On the other hand, learning difficulties and disruptive behavior disorders, which are common in a significant proportion of cases and may be an integral part of the ADHD clinical picture, were not included as exclusion criteria. In line with the literature, the most common comorbid diagnoses in this study were also ODD and SLD, ranking first and second, respectively.

Table 5. Variables with the Highest Weights for the Algorithm with the Best Performance

	FACS	Weight
Video 1 AU12	lip corner pull	0.200
Video 1 AU07	eyelid retractor	0.160
Video 1 AU09	nose curler	0.118
Video 1 AU45	blinking	0.117
Video 1 AU06	cheek lifter	0.116

AU, aAction unite.

Table 6. AU comparisons between Control and ADHD Groups for Video 1

AU	Group	Mean	Standard Deviation	Statistics
AU12	ADHD	29.51	5.65	T: 2.409
	Control	10.58	4.49	*P*: 0.022*
AU07	ADHD	7.50	2.86	T: 1.095
	Control	15.38	7.74	*P*: 0.281
AU09	ADHD	12.92	3.86	T: 5.641
	Control	8.01	2.78	*P*: 0.358
AU45	ADHD	26.18	4.50	T: 1.504
	Control	18.67	3.85	*P*: 0.247
AU06	ADHD	10.41	3.52	T: 2.234
	Control	5.56	3.41	*P*: 0.352

T-Test was used *$P < .05$.
ADHD, attention deficit hyperactivity disorder; AU, Action Unite.

Social Skill Findings

It is known that intelligence level is associated with social functioning and social skill level.[21]Since a direct relationship between social cognition and intelligence level is anticipated, the study design was implemented with all participants consisting of children with normal intelligence and/or above. However, nearly all intelligence subscores of the ADHD group were found to be statistically significantly lower than those of the control group. Therefore, in many statistical analyses, when significant differences were observed between groups, the confounding effect of intelligence was attempted to be controlled. In our study, even when intelligence levels were controlled, both the family- and teacher-completed scales showed that ADHD cases had higher SRS scores than the control group.

Given that the mother's mental state may be directly related to social cognition impairments in children, both genetically and through interaction, the BSI was applied in the study. The total BSI scores of mothers showed a highly significant correlation with the total SRS scores of children. On the other hand, the total BSI score showed a significant correlation only with the ADHD SCALES hyperactivity/impulsivity subscale, excluding SRS. Furthermore, all BSI subtests and total scores showed statistically significant correlations with maternal SRS scores but did not show significant correlations with teacher SRS scores. This finding can be interpreted as indicating that as mothers' BSI scores increase, they perceive their children's SRS scores as more problematic subjectively.

Emotion Recognition Skills Findings

When comparing ADHD and control cases in two groups, the number of correct responses obtained from the DANVA2 test revealed significant differences in various aspects. Although significant differences were observed in low-intensity adult faces, posture recognition, and total scores, these differences disappeared when WISC-R total scores were controlled. This finding suggests that the problems in emotion recognition in posture and percentage observed in ADHD cases may be related to executive functions and intelligence levels, which are also partially part of ADHD. In the literature, there are studies reporting similar results between ADHD cases and control cases in the DANVA2 test and emotion recognition skills.[22-24] On the other hand, many studies have reported that ADHD children have poorer emotion recognition skills than their peers.In one study, preadolescent individuals with ADHD were examined, and it was reported that 74% of them correctly recognized emotions.In that study, accuracy rates decreased as follows: happiness (93.5%), sadness (86%), anger (64.5%), and fear (61%).[25] In this study as well, the ADHD group demonstrated significantly poorer recognition of fearful emotions compared to the control group.

ADHD and Computerized Facial Analysis

Computerized facial analysis has been used in very few studies. Recent computerized facial analysis studies have focused mainly on depression; automatic facial analysis has been shown to be a successful indicator for depression and post-traumatic stress disorder.[26] In a very recent study, important findings were obtained regarding the diagnostic validity of computerized facial analysis as a tool for children with learning disabilities.[2] In the literature, no study has been found that uses computerized facial analysis to track emotional expressions in cases of ADHD.

In our study, the Deep Learning method was the most successful ML algorithm using only AU units. On the other hand, Video 1, which predominantly contained sad emotions, was found to be the most discriminative video for healthy controls and the ADHD group. When examining the discriminative AU units in Video 1, AU12 (lip corner retraction), AU07 (eyelid raising), AU09 (nose wrinkling), AU45 (eye blinking), and AU06 (cheek raising) were the most discriminative features. Based on these results, it can be concluded that, as in Video 1, the most significant changes in children who watched sad expressions were observed in the lips, and that the level of these changes was lower in children with ADHD than in the control group, as seen in AU12. In a recent study comparing SLD and control cases,[2] the groups were compared using computerized facial analysis in terms of differences in AU (facial action units). While watching a video containing sad emotions, AU25 (the muscle unit that pulls the corner of the mouth downward), which indicates a sad facial expression, showed more pronounced movement in healthy controls. Similarly, AU12, which indicates a smiling expression, was more active in controls. The ML analyses revealed that AU2 was the most fundamental variable. AU2 is the projection of the frontalis muscle and functions to lift the outer edge of the eyebrow, with activity occurring in surprise situations. On the other hand, the authors of that study noted that the SLD group showed less AU activity, which could be interpreted as indicating that they understood the emotions in the videos less well.[2] In conclusion, the study reported that the ML model had the ability to distinguish between the SLD and control groups.

Comorbidity and Facial Emotion Recognition

In our study, the high psychiatric comorbidity rate of nearly 70% in the ADHD group reflects the heterogeneous nature of clinical samples. Specifically, children with comorbid SLD demonstrated significantly poorer performance in recognition of emotion from postures and lower total DANVA scores compared to those with ADHD only. This finding aligns with existing literature[27] suggesting that SLD itself involves deficits in FER. Furthermore, our computerized analysis revealed that the control group utilized AU12 (lip corner puller) more actively during emotional stimuli than the ADHD group, suggesting that comorbid neurodevelopmental conditions may further dampen emotional expressivity. These results highlight that FER impairments in ADHD are not only a product of core symptoms but are also significantly exacerbated by the cumulative impact of comorbidities such as SLD.

Limitations

This study has some limitations. First, since this study was conducted on children aged 6-12 years, our findings cannot be generalized to cases of ADHD in adolescence and adulthood. The level of anxiety accompanying ADHD can significantly affect emotion recognition performance and emotion expression. Therefore, anxiety disorders, which frequently co-occur with ADHD, were excluded. However, this means that our findings can only be generalized to cases without co-occurring anxiety disorders. Another limitation of this study is the lack of homogeneity in the socioeconomic characteristics between the participant groups. Specifically, the household income and the education levels of both mothers and fathers were significantly lower in the ADHD group compared to the control group. However, it is important to note that lower educational attainment and, consequently, lower income levels among individuals with ADHD and their parents are frequently reported findings in the existing literature, suggesting that these socioeconomic disparities may be inherent to the nature of the disorder and its intergenerational impact.[28]

On the other hand, despite its limitations, the evaluation of differences in ADHD subgroups and the 2 most common comorbidities in clinical practice, the use of both family and teacher assessments for reliability, and the measurement of face emotion recognition and facial expressions, as well as the evaluation of social responsiveness using 2 separate observer scales, are the strengths of our study.

CONCLUSION

This study is the first to evaluate emotional expressions in ADHD using computerized facial analysis. In addition to emotional expression analysis, emotion recognition and social responsiveness levels, which are very important components of social cognition, were also examined in detail.

When the study findings are evaluated overall, consistent with the hypotheses, the ADHD group showed a lower level of social responsiveness according to both mother and teacher evaluations. When intelligence levels were controlled, this difference remained significant. On the other hand, the significant difference found in DANVA2 total score indicating poorer emotion recognition skills in ADHD disappeared when intelligence levels were controlled. When the ADHD group was divided according to their clinical presentation, children with predominantly inattentive symptoms showed significantly lower performance than the other group in DANVA child faces and overall total scores. When the ADHD group was grouped according to accompanying psychiatric disorders, the group with SLD made significantly more errors in emotion recognition from posture and total scores compared to the others.

According to computerized facial analysis, the deep learning method using only AUs showed the most successful performance. On the other hand, Video 1, which predominantly featured sad emotions, was found to be the most discriminative video for healthy controls and the ADHD group. When the distinctive AU units Video 1 were examined, AU12 (lip corner pulling), AU07 (eyelid raising), AU09 (nose wrinkling), AU45 (eye blinking), and AU06 (cheek raising) were the most distinctive features. The findings of our study can be considered promising for the diagnostic validity of ML methods in ADHD, one of the most common neurodevelopmental disorders.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

Ethics Committee Approval: Ethics committee approval was received for this study from the ethics committee of Ondokuz Mayıs University Clinical Research Ethics Committee, (Date: 16.12.2019, No. B.30.2.ODM.0.20.08/1844-56-992 and decision No. 2018/386).

Informed Consent: Written informed consent was obtained from the participants' parents, and verbal consent was obtained from the children themselves.

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REFERENCES

1. Hall CW, Peterson AD, Webster RE, Bolen LM, Brown MB. Perception of nonverbal social cues by regular education, ADHD, and ADHD/LD students. *Psychol Sch*. 1999;36(6):505-514. (doi:10.1002/(SICI)1520-6807(199911)36:6<505::AID-PITS6>3.0.CO;2-9)
2. Usta MB, Karabekiroğlu K. Computational analysis of affective facial behavior in children with the specific learning disorder. *Anadolu Psikiyatri Derg*. 2020;21(4):1. [CrossRef]
3. Staff AI, Luman M, Van der Oord S, Bergwerff CE, van den Hoofdakker BJ, Oosterlaan J. Facial emotion recognition impairment predicts social and emotional problems in children with (subthreshold) ADHD. *Eur Child Adolesc Psychiatry*. 2022;31(5):715-727. [CrossRef]
4. Olaya-Galindo MD, Vargas-Cifuentes OA, Vélez Van-Meerbeke A, Talero-Gutiérrez C. Establishing the relationship between attention deficit hyperactivity disorder and emotional facial expression recognition deficit: a systematic review. *J Atten Disord*. 2023;27(11):1181-1195. [CrossRef]
5. Kaufman J, Birmaher B, Brent D, et al. Schedule for affective disorders and schizophrenia for school-age children-present and lifetime version (K-SADS-PL): initial reliability and validity data. *J Am Acad Child Adolesc Psychiatry*. 1997;36(7):980-988. [CrossRef]
6. Ercan E, Amado S, Somer O, Çıkoğlu S. A work for developing a test for attention deficit hyperactivity disorder and disruptive behaviours disorders. *Turk J Child Adolesc Ment Health*. 2001;8:132-144.
7. Constantino JN, Przybeck T, Friesen D, Todd RD. Reciprocal social behavior in children with and without pervasive developmental disorders. *J Dev Behav Pediatr*. 2000;21(1):2-11. [CrossRef]
8. Constantino JN, Todd RD. Intergenerational transmission of subthreshold autistic traits in the general population. *Biol Psychiatry*. 2005;57(6):655-660. [CrossRef]
9. GA ÜS, Dedeoğlu C, Taşkın B, Yazgan Y. Social reciprocity in a clinical sample diagnosed with attention deficit hyperactivity disorder: comparison with a control group obtained from a school sample. 19th National Child and Adolescent Psychiatry Congress; 2009.
10. Sahın NH, Batigün AD, Uğurtaş S, Envanteri KS. Güvenilirlik ve faktör Yapisi. *Türk Psikiyatr Derg*. 2002.
11. Wechsler D. *Wechsler Intelligence Scale for Children*; 1949.
12. Nowicki Jr S, Duke MP. Individual differences in the nonverbal communication of affect: the Diagnostic Analysis of Nonverbal Accuracy Scale. *J Nonverbal Behav*. 1994;18(1):9-35. [CrossRef]
13. Nowicki Jr S, Mitchell J. Accuracy in identifying affect in child and adult faces and voices and social competence in preschool children. *Genet Soc Gen Psychol Monogr*. 1998;124(1):39-59.
14. Baltrušaitis T, Robinson P, Morency L-P, eds. Openface: an open source facial behavior analysis toolkit IEEE winter conference on applications of computer vision (WACV); 2016. [CrossRef]
15. Bersani G, Polli E, Valeriani G, et al. Facial expression in patients with bipolar disorder and schizophrenia in response to emotional stimuli: a partially shared cognitive and social deficit of the two disorders. *Neuropsychiatr Dis Treat*. 2013;9:1137-1144. [CrossRef]
16. Steyerberg EW. Validation in prediction research: the waste by data splitting. *J Clin Epidemiol*. 2018;103:131-133. [CrossRef]
17. Hofmann M, Klinkenberg R. *RapidMiner: Data Mining Use Cases and Business Analytics Applications*. CRC Press; Boca Raton; 2016.
18. Reale L, Bartoli B, Cartabia M, et al. Comorbidity prevalence and treatment outcome in children and adolescents with ADHD. *Eur Child Adolesc Psychiatry*. 2017;26(12):1443-1457. [CrossRef]
19. Derks EM, Hudziak JJ, Boomsma DI. Why more boys than girls with ADHD receive treatment: a study of Dutch twins. *Twin Res Hum Genet*. 2007;10(5):765-770. [CrossRef]
20. Sauver JLS, Barbaresi WJ, Katusic SK, Colligan RC, Weaver AL, Jacobsen SJ, eds. Early life risk factors for attention-deficit/hyperactivity disorder: a population-based cohort study. *Mayo Clin Proc*. Elsevier; Amsterdam. 2004;79(9):1124-1131. [CrossRef]
21. Skuse DH, Mandy W, Steer C, et al. Social communication competence and functional adaptation in a general population of children: preliminary evidence for sex-by-verbal IQ differential risk. *J Am Acad Child Adolesc Psychiatry*. 2009;48(2):128-137. [CrossRef]
22. Cadesky EB, Mota VL, Schachar RJ. Beyond words: how do children with ADHD and/or conduct problems process nonverbal information about affect? *J Am Acad Child Adolesc Psychiatry*. 2000;39(9):1160-1167. [CrossRef]

23. Corbett B, Glidden H. Processing affective stimuli in children with attention-deficit hyperactivity disorder. *Child Neuropsychol*. 2000;6(2):144-155. [CrossRef]
24. Greenbaum RL, Stevens SA, Nash K, Koren G, Rovet J. Social cognitive and emotion processing abilities of children with fetal alcohol spectrum disorders: a comparison with attention deficit hyperactivity disorder. *Alcohol Clin Exp Res*. 2009;33(10):1656-1670. [CrossRef]
25. Singh SD, Ellis CR, Winton AS, Singh NN, Leung JP, Oswald DP. Recognition of facial expressions of emotion by children with attention-deficit hyperactivity disorder. *Behav Modif*. 1998;22(2):128-142. [CrossRef]
26. Stratou G, Scherer S, Gratch J, Morency L-P, eds. Automatic nonverbal behavior indicators of depression and PTSD: exploring gender differences Humaine Association Conference on Affective Computing and Intelligent Interaction; 2013. [CrossRef].
27. Operto FF, Pastorino GMG, Stellato M, et al. Facial emotion recognition in children and adolescents with specific learning disorder. *Brain Sci*. 2020;10(8):473. [CrossRef].
28. Kleppesto TH, Eilertsen EM, Van Bergen E, et al. Intergenerational transmission of ADHD behaviors: genetic and environmental pathways. *Psychol Med*. 2024;54(7):1309-1317. [CrossRef].