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Behavioral meaures of psychotic disorders: Using automatic facial coding to detect nonverbal expressions in video

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ABSTRACT

Emotional deficits in psychosis are prevalent and difficult to treat. In particular, much remains unknown about facial expression abnormalities, and a key reason is that expressions are very labor-intensive to code. Automatic facial coding (AFC) can remove this barrier. The current study sought to both provide evidence for the utility of AFC in psychosis for research purposes and to provide evidence that AFC are valid measures of clinical constructs. Changes of facial expressions and head position of participants—39 with schizophrenia/schizoaffective disorder (SZ), 46 with other psychotic disorders (OP), and 108 never psychotic individuals (NP)—were assessed via FaceReader, a commercially available automated facial expression analysis software, using video recorded during a clinical interview. We first examined the behavioral measures of the psychotic disorder groups and tested if they can discriminate between the groups. Next, we evaluated links of behavioral measures with clinical symptoms, controlling for group membership. We found the SZ group was characterized by significantly less variation in neutral expressions, happy expressions, arousal, and head movements compared to NP. These measures discriminated SZ from NP well (AUC = 0.79, sensitivity = 0.79, specificity = 0.67) but discriminated SZ from OP less well (AUC = 0.66, sensitivity = 0.77, specificity = 0.46). We also found significant correlations between clinician-rated symptoms and most behavioral measures (particularly happy expressions, arousal, and head movements). Taken together, these results suggest that AFC can provide useful behavioral measures of psychosis, which could improve research on non-verbal expressions in psychosis and, ultimately, enhance treatment.

1. Introduction

In psychotic disorders, emotional abnormalities are extremely common (Kohler and Martin, 2006) and are associated with a host of poor outcomes, including lower quality of life and worse social functioning (Blanchard et al., 1998). These deficits include abnormal non-verbal emotional expressions, namely blunted affect and inappropriate affect, which are considered characteristic symptoms of schizophrenia (Bleuler, 1911/1950; Kring and Elis, 2013; Kring and Moran, 2008; McGlashan, 2011).[1] Blunted affect is characterized by a decrease variability in spontaneous or elicited expression of emotion (Kirkpatrick et al., 2006). Inappropriate affect is the expression of affect that is incongruent with the circumstance (Andreasen, 1984). Emotional abnormalities are associated with increased risk for psychosis (Gupta et al., 2019; Gupta

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[1] Vocal qualities (e.g., pauses in speech) may also be considered "non-verbal expressions". Here, we focus only on facial coding as an indicator of non-verbal expression. For a review of nonverbal vocal expression in schizophrenia, see Cohen et al. (2014).

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et al., 2023), and are associated with poor outcomes (Blanchard et al., 1998), including conversion to psychosis (Mason et al., 2004). Despite their prevalence and negative associations with outcomes, abnormal non-verbal expressions remain poorly understood (Begue et al., 2020), and there are no effective treatments (Carpenter and Buchanan, 2017). In order to develop more effective treatments, a better understanding of non-verbal expression abnormalities is needed. The current study aimed to elucidate these abnormalities by providing evidence for the utility of automatic facial coding (i.e., AFC) of facial expressions in psychosis for research purposes and to provide evidence that these behavioral measures are valid measures of clinical constructs.

A key reason for the limited understanding of abnormal non-verbal expressions of emotions is the difficulty associated with measuring them (Kohler and Martin, 2006). Historically, their assessment relied exclusively on clinician ratings. While invaluable in many ways, these ratings are largely impressionistic. Consequently, ratings are less likely to capture variability of the patients' expressions over the course of an interaction (Cohen, Cowan, et al., 2020). Also, other information about the patient (e.g., diagnosis, inpatient status) can bias interviewers. The "gold standard" for measurement of facial expressions in research settings has been the Facial Action Coding System (FACS; Ekman and Friesen, 1978; Ekman et al., 2002). FACS revolutionized the study of facial expressions by standardizing ratings of "action units", or components of facial expressions", which allowed for meaningful comparisons between patient groups or between emotion expression types within a patient group. However, FACS, and its companion system, Emotion FACS (Friesen and Ekman, 1983), generally rely on time-consuming ratings made by extensively trained raters, making it difficult to implement broadly.[2] Electromyography (EMG) is another way to measure facial movements. Although sensitive to subtle facial movements, EMG is very obtrusive and may draw participants' attention towards their face, making them aware of changes in their expressions (Ekman et al., 1992). In contrast, AFC offers to capture nuances of facial expressions while maximizing efficiency and minimizing some potential biases (Hamm et al., 2011; Wang et al., 2008).

Applications of AFC to psychopathology are growing (Maithri et al., 2022; e.g., major depressive disorder; Girard et al., 2013), but to date, few investigations included individuals with psychosis (Cowan et al., 2022). However, there is some initial evidence of AFC validity in this population. Research suggests that the frequency of pleasant expressions measured by AFC for individuals with psychosis is lower compared to individuals without psychosis and is negatively correlated with negative symptom severity (Cohen, Cowan, et al., 2020; Tron et al., 2016). In addition, prior studies have found significant associations between head position variability/body movement measured by AI and clinician-rated negative symptoms (Abbas, Yadav, et al., 2021; Chakraborty et al., 2017; Park et al., 2009). Nevertheless, the relations between AFC and a variety of clinical features have not been studied systematically, leaving it unclear the extent to which AFC is associated with other symptoms (e.g., disorganization, depression). Thus, the current study sought to extend previous work by assessing relations between AFC and these hallmarks of psychotic disorders.

There is also some recent support for the validity of AFC in terms of its ability to aid in differentiating groups, an area clinicians and clinical researchers are striving to improve (Bromet et al., 2011). Abbas, Yadav, et al. (2021) reported that an AI measure of head movement variability significantly differentiated those with schizophrenia (n = 17) from control participants (n = 9), supporting the validity of AFC as an indicator of abnormal expressions. Despite this promising finding, the sample was small, leaving the extent to which AFC can distinguish some groups unclear. Thus, the current study aimed to replicate and extend this work by including a larger sample of individuals with different psychotic disorders and clinical features.

Taken together, there is preliminary support for the utility of AFC in psychosis research (e.g., minimizing time spent coding facial expressions) and for the validity of AFC as an indicator of some clinical symptoms. Overall, the current study aimed to elucidate our understanding of non-verbal expression abnormalities by providing additional evidence for the utility of AFC in psychosis for research purposes and to provide evidence that these behavioral measures are valid measures of clinical constructs. Given that variability in expression is expected during a clinical interview (Ekman, 1964; Troisi et al., 2007; Villanueva-Valle et al., 2021), we examined schizophrenia spectrum disorders, other psychotic disorders, and never psychotic individuals video recorded during such an interview. First, we examined the behavioral measures of psychotic disorders using AFC. Given robust evidence of facial expression abnormalities in schizophrenia specifically (Gaebel and Wolwer, 2004; Kohler, Martin, Milonova, et al., 2008; Kohler, Martin, Stolar, et al., 2008), we hypothesized that behavioral measures would discriminate the groups of individuals with schizophrenia spectrum disorders from never psychotic individuals. Next, we tested for relations between behavioral measures and clinician-rated symptoms. Based on theory and previous findings available from both the AFC and broader facial expression literature, we predicted that 1) lower variability in arousal (i.e., the extent to which a person's face was active), head movement, and happy expressions would be related to clinician-rated inexpressivity and avolition (e.g., Cohen, Cowan, et al., 2020); 2) lower variability in arousal and happy expressions and higher variability in anger and sad expressions would be related to depression (Brozgold et al., 1998; Bylsma et al., 2008; Davies et al., 2016; Girard et al., 2013; Jeganathan et al., 2022; J. Rottenberg et al., 2005); 3) variability in head movement would be related to clinician-rated abnormal movements and disorganization (Walther et al., 2014); and 4) clinician-rated disorganization would be related to variability in facial expressions that are atypical for the interview context (anger, fear, disgust, and surprise). We also predicted that variability in arousal, head movement, and happy expressions would differ between the groups (SZ $<$ OP $<$ NP) (e.g., Bishay et al., 2018; Brozgold et al., 1998; Cohen, Cowan, et al., 2020; Kohler, Martin, Milonova, et al., 2008; Kring and Neale, 1996; Kupper et al., 2010). There is no clear evidence that reality distortion is related to specific facial expression abnormalities using automated methods (for a review, see Jiang et al., 2022); thus, we did not expect to find associations with behavioral measures.

2. Material and methods

2.1. Participants

Data were drawn from the 25-year follow-up of the Suffolk County Mental Health Project, a longitudinal study of first-admission psychosis (Bromet et al., 1992, 2011; Fett et al., 2020). The 25-year follow-up included 569 participants. As previously described (Bromet et al., 2011), diagnoses were made by the consensus of study psychiatrists at 20-year follow-up using all available information, including medical records, significant other interviews, and the Structured Clinical Interview for DSM- IV (First et al., 1997).

Analyzable video data were available for 39 individuals with a schizophrenia spectrum diagnosis (schizophrenia or schizoaffective disorder; SZ group), 46 individuals with other psychotic disorders (OP group), and 108 never-psychotic (NP group) adults (N = 193). OP group included bipolar disorder (n = 29), major depression (n = 6), substance induced (n = 4), and other psychoses (brief reactive psychosis, delusional disorder, and psychosis NOS; n = 7). The most common reason that data were unavailable for the current study was because interviews took place over the phone. Table 1 contains demographic information and descriptive statistics for all the measures used in the current study.

[2] There are a growing number of automated procedures that use action units described in the FACS system. Among them is FaceReader, a well validated and commonly employed automated facial coding method, used in the current study.

Table 1
Descriptive information on all measures.

	Schizophrenia Group (SZ; n = 39)	Other Psychoses Group (OP; n = 46)	Never Psychotic Group (NP; n = 108)	SZ vs. NP	SZ vs. OP	OP vs. NP
	Mean (SD) or %			Cohen's *d*; *p* values		
Demographics						
Women	44%	43%	48%	p = 0.63	p = 0.99	p = 0.60
White	84%	91%	92%	p = 0.20	p = 0.36	p = 0.88
Age	52.33 (8.39)	52.96 (9.30)	56.47 (9.01)	−0.47, p = 0.01	−0.07, p = 0.75	−0.39, p = 0.03
Antipsychotics	79%	39%	1%	p < 0.001	p = p < 0.001	p < 0.001
Antidepressants	29%	37%	21%	p = 0.32	p = p = 0.44	p = 0.04
Mood stabilizers	34%	28%	1%	p < 0.001	p = p = 0.56	p < 0.001
AFC Markers*						
Neutral	0.15 (0.04)	0.17 (0.04)	0.17 (0.03)	−0.66, p < 0.001	−0.44, p = 0.04	−0.14, p = 0.42
Happy	0.08 (0.06)	0.10 (0.07)	0.10 (0.07)	−0.42, p = 0.02	−0.38, p = 0.08	−0.03, p = 0.85
Sad	0.09 (0.06)	0.10 (0.08)	0.10 (0.06)	−0.17, p = 0.37	−0.19, p = 0.39	0.04, p = 0.82
Anger	0.01 (0.01)	0.02 (0.02)	0.02 (0.02)	−0.15, p = 0.43	−0.25, p = 0.25	0.10, p = 0.59
Fear	0.03 (0.03)	0.03 (0.03)	0.02 (0.02)	0.23, p = 0.23	0.05, p = 0.81	0.15, p = 0.39
Disgust	0.11 (0.07)	0.12 (0.07)	0.10 (0.06)	0.04, p = 0.84	−0.21, p = 0.33	0.27, p = 0.12
Surprise	0.03 (0.03)	0.03 (0.04)	0.03 (0.03)	−0.18, p = 0.34	−0.20, p = 0.37	0.06, p = 0.75
Valence	−0.13 (0.18)	−0.16 (0.17)	−0.10 (0.14)	−0.19, p = 0.30	0.14, p = 0.53	−0.36, p = 0.07
Arousal	0.06 (0.02)	0.08 (0.03)	0.08 (0.02)	−0.79, p < 0.001	−0.64, p = 0.004	−0.06, p = 0.76
Head movements	12.84 (3.25)	13.95 (3.33)	14.91 (2.96)	−0.68, p < 0.001	−0.34, p = 0.12	−0.31, p = 0.08
Clinician-rated symptoms						
SAPS Reality Distortion	5.16 (7.14)	0.88 (1.76)	0.16 (0.80)	1.36, p < 0.001	0.85, p < 0.001	0.63, p < 0.001
SAPS Disorganization	6.79 (7.28)	3.87 (5.26)	1.61 (3.00)	1.14, p < 0.001	0.47, p = 0.03	0.59, p < 0.001
SANS Avolition	16.16 (6.96)	9.02 (6.41)	4.26 (5.46)	2.02, p < 0.001	1.07, p < 0.001	0.83, p < 0.001
SANS Inexpressivity	9.49 (9.37)	4.02 (5.35)	1.71 (2.98)	1.43, p < 0.001	0.73, p = 0.001	0.60, p < 0.001
Hamilton Depression Rating Scale	7.96 (4.40)	5.96 (4.65)	3.88 (4.70)	0.88, p < 0.001	0.44, p = 0.050	0.45, p = 0.01
Severity of Bodily Movements	0.31 (0.71)	0.09 (0.48)	0.01 (0.10)	0.78, p < 0.001	0.36, p = 0.12	0.29, p = 0.11

Note: *Within-person standard deviations were used for all AFC, except for Valence for which we used its mean. SAPS = Scale for the Assessment of Positive Symptoms; SANS = Scale for the Assessment of Negative Symptoms.

We assert that all procedures contributing to this work comply with the ethical standards of the relevant institutional review board and with the Helsinki Declaration of 1975, as revised in 2008. All participant gave informed consent to participate in study procedures after all were fully explained.

2.2. Measures

2.2.1. Behavioral measures

AFC Measures via *FaceReader*. Participants (N = 240) were video recorded while being interviewed using the Structured Clinical Interview for DSM-IV (SCID; First et al., 1997) and Quality of Life Scale (QLS; Heinrichs et al., 1984). Participants sat facing the interviewer, and the video camera was placed on the desk slightly off center. Participants' data were excluded from analyses if they had less than 10 min of recording where their face could be detected (N = 47). This left 193 participants, with an average of 43.3 min (SD = 24.8) of useable data per participant.

Video recordings were analyzed using FaceReader version 7 (Noldus Information Technology, 2016b), a facial expression analysis software. FaceReader is among the most accurate automated system for emotion detection (Dupre et al., 2020). The algorithms for FaceReader version 7 were developed using Active Appearance Model Training. This procedure is detailed by Kuilenburg et al. (2005). Initial tests of the algorithm found that the classifier was 89% accurate, with accuracy rates from 78% (sad faces) to 99% (happy faces). Subsequent tests found that even in classifying emotions under naturalistic conditions, it was 79% as accurate as human raters. Training samples included over 50,000 photos of individuals who identified as Black, East Asian, Indian, Latino/a, Middle Eastern, Southeast Asian, or White (Noldus, 2023). Thus, FaceReader is a commonly used AFC method, has been validity in several racial/ethnic groups, and has been previously used to examine facial expressions in psychotic disorders (Cohen, Cowan, et al., 2020; Cohen, Schwartz, et al., 2020 Cowan et al., 2022).

FaceReader analyzes individual video frames using deep learning algorithms to estimate to what extent each feature is expressed (Noldus Information Technology, 2016a). The features include emotion expression: neutral, happy, sad, anger, fear, disgust, and surprise. Scores reflect intensity of each specific emotion expression in that frame, ranging from 0 (not at all) to 1 (maximum). For neutral expressions, 0 is highly expressive (i.e., across all emotions) and 1 is completely neutral.

In addition, FaceReader calculates overall arousal and valence of facial expression in the frame. The arousal score indicates the extent to which a participant's face was active during each frame. Arousal is based on the activation of 20 Action Units of the FACS, and ranges from 0 (not active) to 1 (maximally active). The valence score ranges from −1 (intense negative) to +1 (intense positive). It is scored by subtracting the highest intensity negative emotion from intensity of happy in that frame. Finally, FaceReader provides information on head movement/orientation in three dimensions, each expressed as angle ranging from −90 to +90°.

In total, 10 AFC indicators were calculated. Given our interest in emotional expression variability, we analyzed within-person standard deviations of emotional expressions and arousal. For valence, we analyzed a within-person mean, as it indicates the general emotional state of the participant, whereas variability of valence is already captured by variability of its components (specific emotions). Head movement variability was calculated by averaging three within-person standard deviations (one for each dimension).

2.2.2. *Clinician-rated symptoms*

We included six measures of symptoms. Reality distortion, disorganization, inexpressivity, and avolition were scored from the Scale for the Assessment of Positive Symptoms (SAPS; Andreasen, 1984) and Scale for the Assessment of Negative Symptoms (SAPS Andreasen, 1983), rated for the past month. As detailed in Kotov et al. (2016), these four empirical dimensions were derived by a factor analysis of individual SAPS and SANS item scores in the current sample. Each dimension has been shown to be internally consistent, stable across assessments, and have strong discriminant validity. Depressive symptoms were assessed with the Hamilton Depression Rating Scale (HDRS; Hamilton, 1960) Abnormal movements of face, trunk, and extremities indicative of

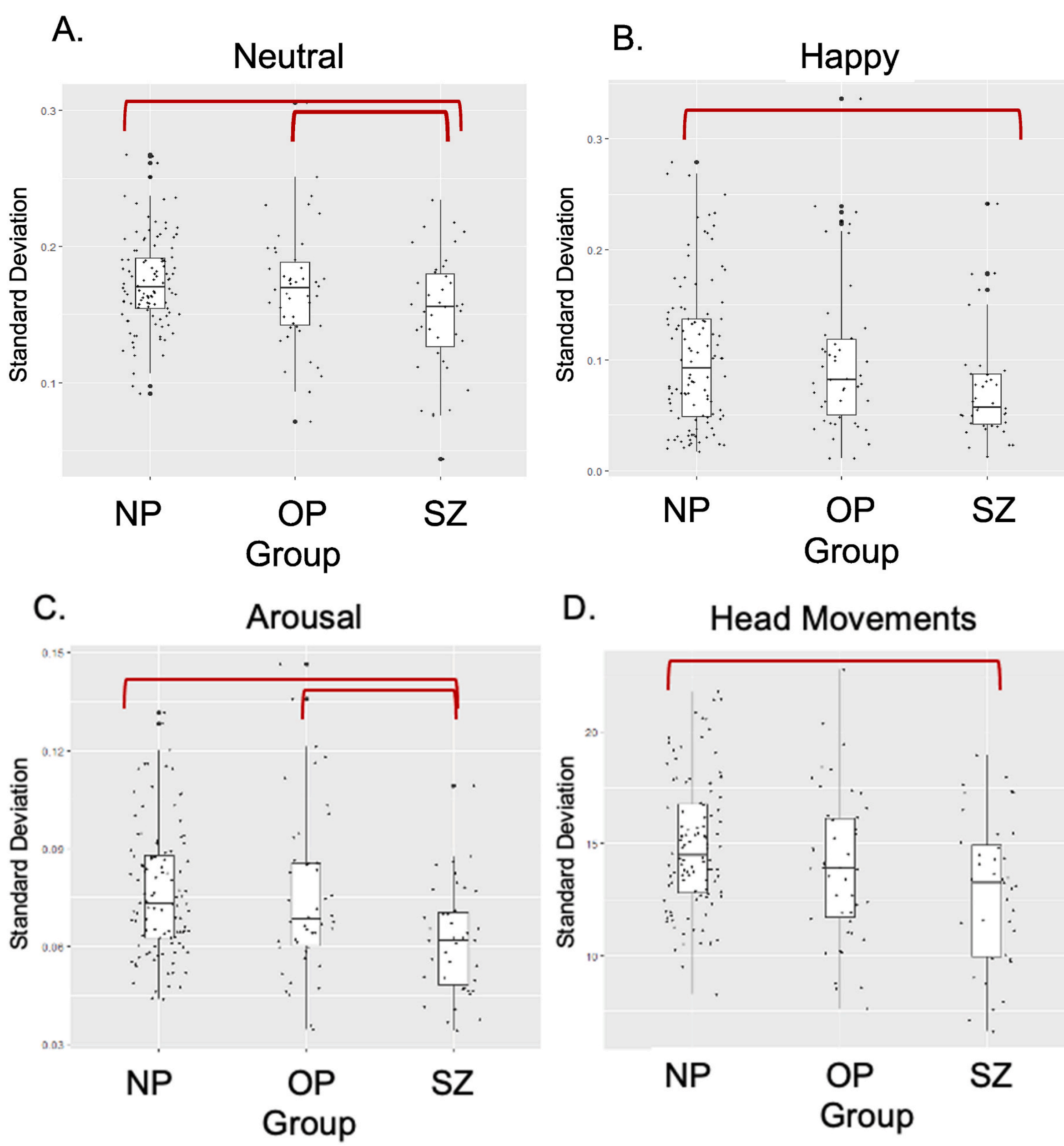

Fig. 1. Box Plots of Behavioral Markers by Group A. Neutral B. Happy C. Arousal D. Head Movements Note. Scales differ between plots because to the variances of behavioral markers. NP = never psychotic group, OP = other psychoses group, SZ = schizophrenia group; Red bars indicate significant group differences.

tardive dyskinesia were assessed via a standardized exam, the Abnormal Involuntary Movement Scale (Guy, 1976). We analyzed global ratings that ranged from 0 (none) to 4 (severe).

2.3. Data analysis

First, we examined behavioral measures of the psychotic disorder groups by testing for group differences on each AI-based behavioral measure. Next, we used logistic regression with forward entry to determine whether the behavioral measures could discriminate between the groups (SZ vs. NP; OP vs. NP). All measures were standardized and only statistically significant predictors were retained. Performance for the resulting model was evaluated using the area under the receiver operating characteristic curve (AUC), and sensitivity and specificity were computed from an optimal cut-off point from the curve. This procedure allowed us to first compare all measures at the same time (i.e., the totality of facial expression abnormalities) and then to use only significant ones to discriminate between groups. Last, controlling for group membership, we examined associations between the 10 behavioral measures and each clinician-rated symptom as well as medication use and comorbid diagnoses. For non-hypothesized relations, we applied a false discovery rate correction (10%; Thissen et al., 2002).

3. Results

3.1. Behavioral measures of psychotic disorders

We first examined the behavioral measures of the psychotic disorder groups. As can be seen in Table 1 and Fig. 1 (A-D), the SZ group showed significantly less variation in neutral expressions, happy expressions, arousal, and head movement compared to the NP group (Cohen's $ds =$ 0.42–0.79, all $ps < 0.05$). In addition, the SZ group showed significantly less variation in neutral expressions and arousal compared to the OP group (Fig. 1A and 1C; Cohen's $ds = 0.44$ and 0.64, $ps < 0.05$). The OP group did not show any significant differences from the NP group, Cohen's $ds \leq |0.36|$, $ps > 0.07$. Taken together, these results suggest that the SZ group has a unique set of behavioral measures compared to the other groups.

3.2. Using behavioral measures to discriminate between groups

We used logistic regression to determine whether the behavioral measures could discriminate between the SZ from the NP group (Table 2). Using forward entry, three behavioral measures were significant in predicting group membership—variations in fear expressions, arousal, and head movement. The AUC was 0.79, indicating that these measures were moderately accurate in discriminating between the SZ and NP groups(Streiner and Cairney, 2007). As can be seen in Fig. 2a, optimal cut-point produced sensitivity of 0.79 and specificity of 0.67.

We used the same procedure to test whether the behavioral measures could discriminate between the SZ and OP groups (Table 2). Variation in arousal was the lone significant measure. The AUC was 0.66, indicating that the curve had a low accuracy in discriminating between the SZ and OP groups (Streiner and Cairney, 2007). As can be seen in Fig. 2b, optimal cut-point produced good sensitivity (0.77) but weak specificity (0.46).

As exploratory tests, we ran two additional logistic regressions to test whether age or sex could discriminate between the groups. In the logistic regression used to determine whether the behavioral measures could discriminate between the SZ from the NP group, age (but not sex) was a significant predictor. Variations in fear expressions, arousal, and head movement remained significant predictors, and the AUC was 0.83. In addition, we found that neither age nor sex were significant predictors in the logistic regression used to test whether AFC measures could discriminate between the SZ and OP groups. Variation in arousal remained the lone significant measure, and the AUC was 0.67. See supplementary materials for these ROC curves.

Table 2
Prediction of group membership from behavioral markers.

	Odds Ratio	R^2
Schizophrenia vs Never Psychotic		0.19
Fear expressions	2.00	
Arousal	0.32	
Head movements	0.61	
Schizophrenia vs Other Psychoses		0.10
Arousal	0.50	

Note: Final block of the models shown; R^2 values are Cox and Snell.

3.3. Associations between behavioral measures and clinician-rated symptoms

Controlling for group status, we examined the associations between behavioral measures and clinician-rated symptoms (Table 3). As predicted, we found that lower variability in arousal (i.e., the extent to which a person's face was active) was related to clinician-rated avolition and depression. Depression was also related to higher variability in angry expressions. As predicted, negative symptoms (avolition and inexpressivity) were related to variability in happy expressions, while clinician-rated disorganization was related to variability in fear and surprise expressions and head movements. Also, as predicted, clinician-rated abnormal movements were also related to head movements. The correlations ranged from small to moderate ($|0.15|$ to $|0.30|$). Last, as predicted, clinician-rated reality distortion was not related to any behavioral measure after a false discovery rate correction was applied.

As can be seen in Table 3, a few non-predicted relations were statistically significant but only one of these remained significant after a false discovery rate correction was applied (valence and inexpressivity).

3.4. Associations of behavioral measures with medication and comorbid diagnoses

To test whether medication use was related to facial expressions in the current sample, we examined correlations between current antipsychotic medication, current antidepressant medication, and current mood stabilizer use (yes or no) with each of the automatic facial coding (AFC) measures in individuals with a psychotic disorder diagnosis. We controlled for diagnosis (schizophrenia, other psychotic disorder) given different rates of usage of these medications between the groups (see Table 1). All correlations were small in size and non-significant (all $rs \leq$ 0.20, all $ps \geq 0.07$), with one exception (mood stabilizer use with sad expressions, $r = 0.25$, $p = 0.02$). This relation was no longer significant after a false discovery rate was applied.

To test whether comorbid diagnoses were related to facial expressions in the current sample, we examined correlations between a major depressive disorder diagnosis, substance use diagnosis, and any anxiety disorder diagnoses over the previous 10 years with each of the AFC measures in individuals with a psychotic disorder diagnosis. After applying a false discovery rate correction, all correlations were small in size and non-significant, with one exception (substance use disorders with head movement, $r = 0.5$, $p = 0.001$). See supplementary materials for all correlations.

4. Discussion

The extent of the universality of facial expression has been challenged (e.g., Barrett, 2006) with compelling rebuttals to these challenges (e.g., Cowen et al., 2021). However, there seems to be agreement that facial expressions convey a range of information, including information about how one feels. The current study sought to increase our

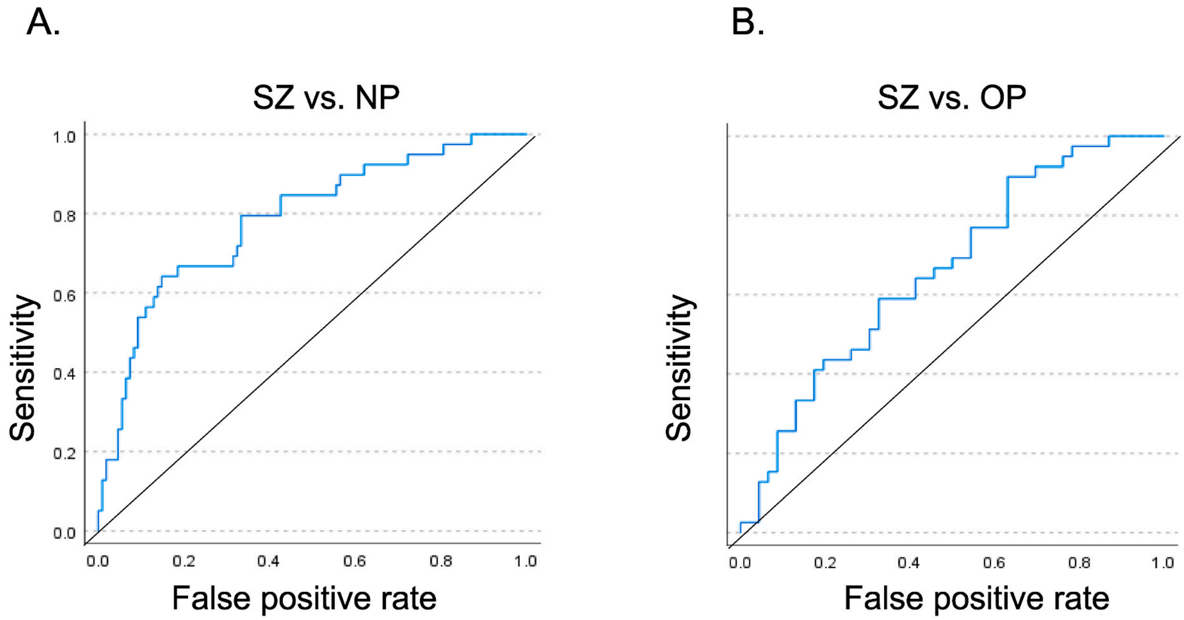

Fig. 2. ROC Curves for Behavioral Markers to Discriminate between Groups A. AUC = 0.79, cut-point = 0.23, sensitivity = 0.79, specificity = 0.67 B. AUC = 0.66, cut-point = 0.43, sensitivity = 0.77, specificity = 0.46 Note. False positive rate = 1 – specificity.

Table 3
Partial correlations of AFC with symptom, functioning, and physical assessment measures controlling for group status ($N = 193$).

	Neutral	Happy	Sad	Anger	Fear	Disgust	Surprise	Valence	Arousal	Head Movements
1. SAPS Reality Distortion	−0.10	−0.04	0.03	0.01	0.14	−0.09	0.05	0.03	0.01	0.08
2. SAPS Disorganization	−0.12	−0.15*	−0.04	0.01	0.22**	0.02	0.30***	−0.07	−0.02	0.27***
3. SANS Avolition	−0.15*	−0.15*	0.09	−0.04	−0.08	0.04	−0.04	−0.08	−0.18*	0.03
4. SANS Inexpressivity	−0.09	−0.16*	0.05	−0.06	0.01	0.05	−0.15*	−0.18*	−0.07	−0.04
5. Hamilton Depression Rating Scale	−0.08	−0.04	−0.02	0.18*	0.03	0.06	0.08	−0.04	−0.15*	0.12
6. Severity of abnormal movements	−0.05	−0.01	−0.16*	−0.04	0.02	0.00	0.14	−0.03	−0.07	−0.19*

Note: and ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$; SAPS = Scale for the Assessment of Positive Symptoms; SANS = Scale for the Assessment of Negative Symptoms; IDAS = Inventory for Depression and Anxiety Symptoms. Within-person standard deviations were used for all AFC, except for Valence for which we used its mean.

understanding of expression abnormalities in psychotic disorders by using well validated, widely accepted artificial intelligence detectors of non-verbal expression (AFC). Overall, results indicate that 1) AFC can identify behavioral measures for schizophrenia spectrum disorder, and 2) these measures can discriminate individuals with this disorder from never psychotic individuals fairly well, although not sufficient for clinical applications currently, and 3) some AFC measures are associated with clinician-rated symptoms. There were small, mostly non-significant correlations for medication use and comorbid diagnoses with AFC measures, suggesting little relations between these potential confounders and facial expressions in the current study.

As we expected, the SZ group had a unique set of AFC measures. Compared to never psychotic individuals, people with schizophrenia spectrum disorders showed significantly less variation in neutral expressions, happy expressions, arousal, and head movement. This is consistent with work using AFC (Cohen, Cowan, et al., 2020; Tron et al., 2016) and human raters (Gaebel and Wolwer, 2004; Kohler, Martin, Milonova, et al., 2008; Kohler, Martin, Stolar, et al., 2008) that has shown that individuals with schizophrenia show less facial expressivity and less movement overall compared to unaffected adults. Emotional abnormalities are extremely common in schizophrenia spectrum disorders (Kohler and Martin, 2006), are associated with increased risk for psychosis (Gupta et al., 2019), and are associated with poor outcomes (Blanchard et al., 1998), including conversion to psychosis (Mason et al., 2004). Despite their prevalence and negative associations with outcomes, abnormal non-verbal expressions remain poorly understood (Begue et al., 2020), The current work suggests that AFC can increase our understanding of non-verbal expression abnormalities in order to ultimately inform prevention and intervention efforts.

In contrast to the SZ group, no clear set of measures emerged for the group with other psychotic disorders. This group did not differ significantly from the never-psychotic group on any of the measures. Measures other than facial expression alone (e.g., upper body movements; Mittal et al., 2008) may be necessary in order to characterize other psychotic disorders.

Jointly, behavioral measures differentiated schizophrenia spectrum disorders from the never-psychotic group reasonably well, evidenced by fairly high AUC (Streiner and Cairney, 2007) and good sensitivity and specificity (adding demographic variables had little effect on the AUC). Of note, variability in fear expressions was a particularly strong predictor. Although there is evidence that perception or recognition of fear expressions in others may be impaired in schizophrenia (for a review, see Barkl et al., 2014), there is a lack of evidence that expressing fear via the face is impaired in this group (Kohler, Martin, Milonova, et al., 2008; Kohler, Martin, Stolar, et al., 2008). At the same time, an expression of fear in this interview context would be atypical. Thus, it is possible that although individuals with schizophrenia may be impaired at recognizing fear expressions in others, there is not an equivalent impairment in making these expressions themselves. Further, they may be more likely to make such expressions in an atypical context, leading fear expressions to be a particularly useful predictor of group membership in the current study.

These effect sizes are too small to be useful clinically but indicate potential utility for translational research and fundamental science of emotion. The main goal for this area of research is the development of objective and scalable assessment of certain fundamental symptoms and behavioral deficits of psychotic disorders. Indeed, the observed nonverbal measures in the current study are consistent with robust previous findings of facial expression abnormalities in schizophrenia (Gaebel and Wolwer, 2004; Kohler, Martin, Milonova, et al., 2008; Kohler, Martin, Stolar, et al., 2008). However, behavioral measures were worse at distinguishing schizophrenia spectrum from other psychotic disorders with low AUC and a difference in only one measure (arousal). Clearly, there is more work to be done in this area but the current results provide promise regarding research applications of AFC.

As predicted, we also found a number of associations between behavioral measures and clinician-rated symptoms. Even controlling for group status, these associations were small to moderate in size. As we hypothesized, behavioral measures, including happy expressions and arousal, were related to clinician-rated negative symptoms. This suggests there is an overall blunting in SZ, a finding consistent with non-AFC studies of posed and evoked facial expression in SZ (e.g., Kohler, Martin, Milonova, et al., 2008; Kohler, Martin, Stolar, et al., 2008; Tremeau et al., 2005). Also as hypothesized, greater depression was associated with decreased arousal. This is consistent with findings documented in the non-AFC literature (J. Rottenberg et al., 2005; Jonathan Rottenberg and Vaughan, 2008). We also found that depression was associated with increased anger expression variability, consistent with previous research reporting an association between depression and negative facial expressions (e.g., contempt; Berenbaum, 1992; Girard et al., 2013; Jaeger et al., 1986; Sloan et al., 1997). Variability in head movements was correlated with disorganization and clinician-rated abnormal movements, in line with some prior work linking clinician-rated disorganization and an objective measure of variability in motor activity (Walther et al., 2014). Disorganization was also associated with more variability in fear and surprise expressions, expressions that are atypical in the interview setting. In addition, the current findings are consistent with initial previous research that has reported associations between AFC and symptoms (Abbas, Yadav, et al., 2021; Chakraborty et al., 2017; Cohen, Cowan, et al., 2020; Park et al., 2009; Tron et al., 2016), and taken together, suggest that AFC can be valid indicators of outcomes of interest to researchers and clinicians alike. Although tentative, the current pattern of findings provides some evidence for the validity of AFC as potentially helpful additions to clinical ratings. This pattern includes 1) the link of variability in arousal with clinician-rated avolition and depression but not clinician-rated disorganization and reality distortion; 2) the link between head movements with clinician-rated disorganization and severity of abnormal movements but not reality distortion; 3) the link of variability in happy expressions to clinician-rated inexpressivity and avolition but not reality distortion; and 4) the link between variability in arousal and anger expressions to depression but not reality distortion. Again, although preliminary, the current work, coupled with other related work (e.g., Loch et al., 2023), suggest possible clinical applications. As discussed below (Limitations section), future research is needed in order to replicate the current findings in other settings and in samples with different demographic characteristics.

Overall, the current findings have several broad implications for research. First, a key reason for our limited understanding of abnormal facial expressions of emotions is the difficulty associated with measuring them (Kohler and Martin, 2006). AFC are objective measures of psychotic symptoms that can complement clinician ratings. They can be easily implemented as they do not required extensive training nor time-consuming coding (Cross et al., 2022). Thus, AFC can facilitate research because it can capture nuances of facial expressions while maximizing efficiency and minimizing potential biases (Hamm et al., 2011; Wang et al., 2008). Second, it is scalable given its automaticity and may be more sensitive to treatment effects as AFC could detect subtle nuances unobservable to clinicians. Also, AFC does not require blinding, making it a promising tool for randomized clinical trials (Abbas, Sauder, et al., 2021; Harati et al., 2020). In addition, although we used basic emotions in the current study, AFC can be trained for specific applications (e.g., measure severity of affective blunting), using rich information on individual action units (movement of specific muscles) and temporal dynamics (beyond simple variability), thus substantially increasing their accuracy. This modeling requires much larger samples than available in the present project and is an important target for future research. The current findings also have clinical implications for diagnostics and treatment. The observed effects are too small for AFC to replace clinical ratings, but as AFC develops further, it may be able to augment these ratings to assist clinicians in making a psychotic disorder diagnosis and in detecting symptom worsening or improvement, which would signal a need to adjust treatment.

Limitations. In this study, we used FaceReader, a commonly used method for facial expression analysis. Although it is among the most accurate automated system for emotion detection (Dupre et al., 2020) and has a very high accuracy rate compared to human raters, it was not developed for use in clinical samples. Thus, it is possible that the facial expressions of clinical samples are less accurately identified. Also, given the proprietary nature of FaceReader, it is not possible to independently verify its algorithms. Future research could use other, non-propriety software to replicate the current findings.

Although, to our knowledge, this is the largest sample of individuals with psychosis to investigate AFC, and an average of 43.3 min of video was available per subject, some expressions were infrequent, particularly disgust. This limited our statistical power in testing for associations, as well as identifying them as behavioral measures of psychosis. We investigated video taken during a clinical interview, which increases applicability of present findings to diverse settings, but this context may have created a more limited range of expressions. Thus, future research could employ AFC during a range of situations, such as telemedicine visits or live social interaction lab tasks (Martin et al., 2019), to examine whether behavioral measures might be different across contexts. Also, although tardive dyskinesia was measured in our sample, there were not separate assessments of other atypical movements, such as Parkinsonism or akathisia. Future research could include these additional assessments to control for any effect on facial expressions. As our study was focused on psychotic disorders and utilized a sample comprised of predominately white males, it is unclear whether results will generalize to individuals with other forms of psychopathology or demographic characteristics. Future research is needed in order to test whether these results generalize to other groups, to determine the test-retest reliability of AFC in these populations, and to perform cross-validation work.

5. Conclusions

Despite these limitations, the current work demonstrates that 1) AFC can be used to characterize behavioral measures of psychotic disorders, 2) these measures can discriminate between individuals with schizophrenia spectrum disorder from never psychotic individuals, and 3) these measures are associated with clinician-rated symptoms. Although current findings suggest that clinical practice would benefit from the development of more powerful AFC, AFC is ripe for application to research settings.

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Elizabeth A. Martin: Formal analysis, Writing – original draft. **Wenxuan Lian:** Formal analysis. **Joshua R. Oltmanns:** Formal analysis, Methodology. **Katherine G. Jonas:** Conceptualization, Supervision, Writing – review & editing. **Dimitris Samaras:** Methodology. **Michael N. Hallquist:** Investigation. **Camilo J. Ruggero:** Investigation. **Sean A.P. Clouston:** Investigation. **Roman Kotov:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing.

Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpsychires.2024.05.056.

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