

Running title: BEHAVIORAL MARKERS AND nveAI

Behavioral Markers of Psychotic Disorders:
Using Artificial Intelligence 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. Artificial intelligence measures of non-verbal expressions (nveAI) can remove this barrier. The current study sought to increase understanding of facial expression abnormalities in psychotic disorders by using nveAI. 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 markers of the psychotic disorder groups and tested if they can discriminate between the groups. Next, we evaluated links of behavioral markers with clinical features (symptoms, functioning, and physical performance) controlling for group membership. We found the SZ group was characterized by significantly less variation in neutral expressions, happy expressions, arousal, and head orientation compared to NP. These markers discriminated SZ from NP well (AUC=.79, sensitivity=.79, specificity=.67) but discriminated SZ from OP less well (AUC=.66, sensitivity=.77, specificity=.46). We also found significant correlations between clinical features and all behavioral markers (particularly happy expressions, arousal, and head orientation), except disgust. Taken together, these results suggest that nveAI can provide useful behavioral markers of psychosis, which could improve research on non-verbal expressions in psychosis and, ultimately, enhance treatment.

Keywords: facial expressions, emotional expressions, schizophrenia, flat affect, depression, FaceReader

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). Blunted affect is characterized by a decrease in 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). Blunted and inappropriate affect precede the onset of psychosis (Gooding et al., 2018; Gupta et al., 2019) and can predict the development of a psychotic illness (Mason et al., 2004; Schmidt et al., 2017). 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 employing artificial intelligence measures of non-verbal expressions (i.e., nveAI) to determine behavioral markers of psychosis.

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 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, 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), rely on time-consuming ratings made by extensively trained raters, making it difficult to implement broadly. 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, nveAI offers to capture nuances of facial expressions while maximizing efficiency and minimizing potential researcher/participant biases (Hamm et al., 2011; Wang et al., 2008).

Applications of nveAI 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 nveAI validity in this population. Research suggests that the frequency of pleasant expressions measured by nveAI for individuals with psychosis is lower compared to individuals without psychosis and is negatively correlated with negative symptom severity (Cohen 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 et al., 2021b; Chakraborty et al., 2017; Park et al., 2009). Nevertheless, the relations between nveAI and a variety of clinical features have not been studied systematically, leaving it unclear the extent to which nveAI is associated with other symptoms (e.g., disorganization, depression), everyday

functioning, and physical performance. Thus, the current study sought to extend previous work by assessing relations between nveAI and these hallmarks of psychotic disorders.

There is also some recent evidence that nveAI can support diagnostic decision-making, an area clinicians and clinical researchers are striving to improve (Bromet et al., 2011). Abbas and colleagues (2021b) reported that an AI measure of head movement variability significantly differentiated those with schizophrenia ($n = 17$) from control participants ($n = 9$), suggesting that AI could accurately classify participants by diagnosis. Despite this promising finding, the sample was small, leaving the extent to which nveAI can be used to aid in diagnosis of psychotic disorders 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.

Overall, the current study sought to increase our understanding of non-verbal expression abnormalities by using AI to identify behavioral markers of psychosis. 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 markers of psychotic disorders using nveAI. Given robust evidence of facial expression abnormalities in schizophrenia specifically (Gaebel and Wolwer, 2004; Kohler et al., 2008a; Kohler et al., 2008b), we hypothesized that behavioral markers would discriminate the groups of individuals with schizophrenia spectrum disorders from never psychotic individuals. Next, we tested for relations between behavioral markers and a variety of clinical features, including symptoms, everyday functioning, and physical performance. Given this small, nascent literature, we had only a few specific hypotheses. Based on previous findings available from both the AI and broader facial expression literature (Brozgold et al., 1998; Cohen et al., 2020; Girard

et al., 2013; Kupper et al., 2010; Matsumoto et al., 2008; Rottenberg and Vaughan, 2008), we predicted that low variability in expressions would be related to clinician-rated inexpressivity and depression, and head movement would be related to clinician-rated abnormal movements.

2. Materials 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., 2011; Bromet et al., 1992; 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). Table 1 contains demographic information and descriptive statistics for all the measures used in the current study.

The most common reason that data were unavailable for the current study was because interviews took place over the phone. There were no differences on any demographic or clinical variables (i.e., symptom, functioning, physical performance) between those in the current study versus those not in the current study for any diagnostic group with a single exception. NP

participants in the current study were slightly more depressed than NP participants not in the current study ($d = 0.31, p = .03$).

2.2 Measures.

2.2.1 Behavioral Markers

nveAI Markers 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 minutes of recording where their face could be detected ($N = 47$). This left 193 participants, with an average of 43.3 minutes ($SD = 24.8$) of usable data per participant.

Video recordings were analyzed using FaceReader version 7 (2018), a facial expression analysis software. FaceReader is among the most accurate AI for emotion detection (Dupre et al., 2020). Even in classifying emotions under naturalistic conditions, it was 79% as accurate as human raters. Thus, it is a widely accepted nveAI method.

FaceReader analyzes individual video frames for landmark features, and using proprietary deep learning algorithms, the software then integrates these features and determines the extent to which these features in each frame characterize an emotion expression (neutral, happy, sad, anger, fear, disgust, and surprise). Scores reflect intensity of each specific emotion expression is shown during that frame, ranging from 0 (not at all) to 1 (maximum). In addition to specific emotion expressions, FaceReader calculates overall valence and arousal scores. The valence score is a dimension of emotional expression ranging 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. 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 range in scores from 0 (not active) to 1 (active). Finally, FaceReader provides information on head orientation in three dimensions, each expressed as angle ranging from -90 to +90 degrees.

In total, 10 nveAI indicators were calculated. Given our interest in emotional expression variability, we analyzed within-person standard deviation of each marker, with the exception of valence. For valence, we analyzed 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 orientation variability was calculated by averaging three within-person standard deviations (one for each dimension).

2.2.2 Clinical Features

2.2.2.1 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 (SANS; 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). Last, we included full symptom remission defined according to consensus criteria (2005), which requires ratings of mild or less on all global items of the SAPS and SANS.

2.2.2.2 Functioning. We included two measures of functioning. Use of public assistance was coded as 0 = no and 1 = yes (e.g., SSI, SSD, welfare, rent supplements, food stamps). As detailed previously (2021), recovery status at the 25 year follow-up was defined according to the criteria of Liberman et al. (2002) which requires ratings of 4 or less on multiple items from the Brief Psychiatric Rating Scale (Overall and Gorham, 1988) as well as ratings of 2 or more on items assessing occupational and social functioning from the QLS (Heinrichs et al., 1984).

2.2.2.3 Physical Performance. Two measures of physical performance were included. Abnormal movements of face, trunk, and extremities indicative of tardive dyskinesia were assessed via a standardized exam, the Abnormal Involuntary Movement Scale (1976). We analyzed global rating that ranged from 0 (none) to 4 (severe). The Short Physical Performance Battery (Guralnik et al., 1994) was used to assess extremity functioning (rising from a chair, balancing while standing, and gait speed). Total scores on the battery range from 0 to 12, with higher scores indicating better functioning.

2.3 Data Analysis. First, we examined behavioral markers of the psychotic disorder groups by testing for group differences on each AI-based behavioral marker. Next, we used logistic regression with forward entry to determine whether the behavioral markers could discriminate between the groups (SZ vs. NP; OP vs. NP). All markers 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. Last, controlling for group membership, we examined associations between the 10 behavioral markers and each clinical feature (symptoms, functioning, and physical performance).

3. Results

3.1 Behavioral Markers of Psychotic Disorders

We first examined the behavioral markers of the psychotic disorder groups. As can be seen in Table 1 and Figure 1 (A-D), the SZ group showed significantly less variation in neutral expressions, happy expressions, arousal, and head orientation compared to the NP group (Cohen's d s \equiv 0.42 – 0.79, all p s $<$.05). In addition, the SZ group showed significantly less variation in neutral expressions and arousal compared to the OP group (Figure 1A, 1C; Cohen's d s \equiv 0.44 and 0.64, p s $<$.05). The OP group did not show any significant differences from the NP group, Cohen's d s \leq |0.36|, p s $>$.07. Taken together, these results suggest that the SZ group has a unique set of behavioral markers compared to the other groups.

3.2 Using Behavioral Markers to Discriminate between Groups

We used logistic regression to determine whether the behavioral markers could discriminate between the SZ from the NP group (Table 2). Using forward entry, three behavioral markers were significant in predicting group membership—variations in fear expressions, arousal, and head orientation. The AUC was .79, indicating that these markers were moderately accurate in discriminating between the SZ and NP groups. (Streiner and Cairney, 2007) As can be seen in Figure 2a, optimal cut-point produced sensitivity of .79 and specificity of .67.

We used the same procedure to test whether the behavioral markers could discriminate between the SZ and OP groups (Table 2). Variation in arousal was the lone significant marker. The AUC was .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 Figure 2b, optimal cut-point produced good sensitivity (.77) but weak specificity (.46).

3.3 Associations between Behavioral Markers and Clinical Features

Controlling for group status, we examined the associations between behavioral markers and clinical features (Table 3). Of these markers, happy expression variability showed the largest number of significant correlations with the clinical features, five altogether. Variability in arousal and head orientation had three significant links each. Variability in fear and surprise, as well as valence, had two significant associations each, and the remaining markers had one, except that variability in disgust had none. The correlations ranged from small to moderate ($|.15|$ to $|.30|$).

Disorganization was associated with more head movement, variability in surprise and fear expression, and less variability in happy expression. Negative symptoms (avolition or inexpressivity) were correlated with less variability in arousal, and surprise and happy expressions as well as more negative valence. Depression was linked to greater anger variability and lower arousal variability. Remission was associated with greater variability of happy expressions and arousal. With regard to everyday functioning, public assistance was associated with more variability in fear and happy expressions, and recovery was related to less head movement. Physical performance revealed that abnormal movements (tardive dyskinesia) were linked to less head movement and sad expression variability. Better physical performance was associated with greater arousal variability.

4. Discussion

The current study sought to increase our understanding of expression abnormalities in psychotic disorders by using well validated, widely accepted artificial intelligence detectors of non-verbal expression (nveAI). Overall, results indicate that 1) nveAI can identify behavioral markers for schizophrenia spectrum disorder, and 2) these markers can discriminate individuals

with this disorder from never psychotic individuals fairly well, although not sufficient for clinical applications currently, and 3) nveAI abnormalities are associated with a variety of clinical features.

As we expected, the SZ group had a unique set of nveAI markers. Compared to never psychotic individuals, people with schizophrenia spectrum disorders showed significantly less variation in neutral expressions, happy expressions, arousal, and head orientation. This is consistent with work using AI (Cohen et al., 2020; Tron et al., 2016) and human raters (Gaebel and Wolwer, 2004; Kohler et al., 2008a; Kohler et al., 2008b) 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), precede the onset of psychosis (Gooding et al., 2018; Gupta et al., 2019), and are associated with poor outcomes (Blanchard et al., 1998), including conversion to psychosis (Mason et al., 2004; Schmidt et al., 2017). Despite their prevalence and negative associations with outcomes, abnormal non-verbal expressions in this population remain poorly understood (Begue et al., 2020). The current work suggests that nveAI 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 markers emerged for the group with other psychotic disorders. This group did not differ significantly from the never-psychotic group on any of the markers. Markers 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 markers 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. These effect sizes are too small to be useful clinically but indicate potential utility for translational research and fundamental science of emotion. Indeed, the observed non-verbal markers are consistent with robust previous findings of facial expression abnormalities in schizophrenia (Gaebel and Wolwer, 2004; Kohler et al., 2008a; Kohler et al., 2008b). However, behavioral markers were worse at distinguishing schizophrenia spectrum from other psychotic disorders with low AUC and a difference in only one marker (arousal).

We also found a number of associations between behavioral markers and a variety of clinical features, including symptoms, functioning, and physical performance. Even controlling for group status, these associations were small to moderate in size. As we hypothesized, several behavioral markers were related to clinician-rated inexpressivity. This suggests there is an overall affective blunting in SZ, a finding consistent with non-nveAI studies of posed and evoked facial expression in SZ (e.g., Kohler et al., 2008a; Kohler et al., 2008b; Tremeau et al., 2005). Also as hypothesized, greater depression was associated with decreased arousal. This is consistent with findings documented in the non-nveAI literature (Rottenberg et al., 2005; 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). Greater disorganization was correlated with increased head movement, in line with some prior work linking clinician-rated disorganization and an objective measure of variability in motor activity (Walther et al., 2014). In addition, the current findings are consistent with initial previous research that has reported associations between AI and symptoms (Abbas et al., 2021b; Chakraborty et al., 2017; Cohen et al., 2020; Park et al.,

2009; Tron et al., 2016), and taken together, suggest that nveAI can be valid indicators of outcomes of interest to researchers and clinicians alike.

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). nveAI are objective markers of psychotic symptoms that can complement clinician ratings. They can be easily implemented as they do not require extensive training nor time-consuming coding (Cross et al., 2022). Thus, nveAI 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 nveAI could detect subtle nuances unobservable to clinicians. Also, nveAI does not require blinding, making it a promising tool for randomized clinical trials (Abbas et al., 2021a; Harati et al., 2020). In addition, although we used basic emotions in the current study, nveAI can be trained for specific applications (e.g., to detect schizophrenia or 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, treatment, and screening. The observed effects are too small for nveAI to replace clinical ratings, but as nveAI 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. In addition, in primary care settings, nveAI may help to detect

symptoms of psychosis that general practitioners are not trained to identify. These applications will require further testing in targeted clinical settings to provide additional evidence of the clinical utility of nveAI.

Although, to our knowledge, this is the largest sample of individuals with psychosis to investigate nveAI, and an average of 43.3 minutes 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 markers 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 nveAI during a range of situations, such as a live social interaction lab task (Martin et al., 2019), to examine whether behavioral markers might be different across contexts.

5. Conclusions

Despite these limitations, the current work is the first to demonstrate that 1) nveAI can be used to characterize behavioral markers of psychotic disorders, 2) these markers can discriminate between individuals with schizophrenia spectrum disorder from never psychotic individuals, and 3) these markers are associated with a variety of clinical features. Although current findings suggest that clinical practice would benefit from the development of more powerful nveAI, nveAI is ripe for application to research settings.

Figure Legend

Figure 1. Box Plots of Behavioral Markers by Group

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

Figure 2. ROC Curves for Behavioral Markers to Discriminate between Groups

A. AUC = .79, cut-point = .23, sensitivity = .79, specificity = .67

B. AUC = .66, cut-point = .43, sensitivity = .77, specificity = .46

Note. False positive rate = $1 - \text{specificity}$

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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 <i>d</i> ; <i>p</i> values		
Demographics						
Women	44%	43%	48%	p = .63	p = .99	p = .60
White	84%	91%	92%	p = .20	p = .36	p = .88
Age	52.33 (8.39)	52.96 (9.30)	56.47 (9.01)	-0.47, p = .01	-0.07, p = .75	-0.39, p = .03
nveAI Markers*						
Neutral	0.15 (0.04)	0.17 (0.04)	0.17 (0.03)	-0.66, p < .001	-0.44, p = .04	-0.14, p = .42
Happy	0.08 (0.06)	0.10 (0.07)	0.10 (0.07)	-0.42, p = .02	-0.38, p = .08	-0.03, p = .85
Sad	0.09 (0.06)	0.10 (0.08)	0.10 (0.06)	-0.17, p = .37	-0.19, p = .39	0.04, p = .82
Anger	0.01 (0.01)	0.02 (0.02)	0.02 (0.02)	-0.15, p = .43	-0.25, p = .25	0.10, p = .59
Fear	0.03 (0.03)	0.03 (0.03)	0.02 (0.02)	0.23, p = .23	0.05, p = .81	0.15, p = .39
Disgust	0.11 (0.07)	0.12 (0.07)	0.10 (0.06)	0.04, p = .84	-0.21, p = .33	0.27, p = .12
Surprise	0.03 (0.03)	0.03 (0.04)	0.03 (0.03)	-0.18, p = .34	-0.20, p = .37	0.06, p = .75
Valence	-0.13 (0.18)	-0.16 (0.17)	-0.10 (0.14)	-0.19, p = .30	0.14, p = .53	-0.36, p = .07
Arousal	0.06 (0.02)	0.08 (0.03)	0.08 (0.02)	-0.79, p < .001	-0.64, p = .004	-0.06, p = .76
Head orientation	12.84 (3.25)	13.95 (3.33)	14.91 (2.96)	-0.68, p < .001	-0.34, p = .12	-0.31, p = .08
Symptoms						
SAPS Reality Distortion	5.16 (7.14)	0.88 (1.76)	0.16 (0.80)	1.36, p < .001	0.85, p < .001	0.63, p < .001
SAPS Disorganization	6.79 (7.28)	3.87 (5.26)	1.61 (3.00)	1.14, p < .001	0.47, p = .03	0.59, p < .001
SANS Avolition	16.16 (6.96)	9.02 (6.41)	4.26 (5.46)	2.02, p < .001	1.07, p < .001	0.83, p < .001
SANS Inexpressivity	9.49 (9.37)	4.02 (5.35)	1.71 (2.98)	1.43, p < .001	0.73, p = .001	0.60, p < .001
Hamilton Depression Rating Scale	7.96 (4.40)	5.96 (4.65)	3.88 (4.70)	0.88, p < .001	0.44, p = .050	0.45, p = .01
Full symptom remission	5%	30%	73%	p < .001	p = .002	p < .001

Functioning						
Public assistance	77%	48%	10%	p < .001	p = .005	p < .001
Recovery	16%	43%	76%	p < .001	p = .007	p < .001
Physical Performance						
Severity of Bodily Movements	0.31 (0.71)	0.09 (0.48)	0.01 (0.10)	0.78, p < .001	0.36, p = .12	0.29, p = .11
Short Physical Performance Battery - Total	9.13 (2.35)	10.03 (1.95)	10.46 (1.77)	-0.69, p = .001	-0.42, p = .09	-0.24, p = .23

Note: *Within-person standard deviations were used for all nveAI, 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

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 orientation	0.37	
Schizophrenia vs Other Psychoses		0.10
Arousal	0.50	

Note: Final block of the models shown; R² values are Cox and Snell

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

	Neutral	Happy	Sad	Anger	Fear	Disgust	Surprise	Valence	Arousal	Head Orientation
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. Full symptom remission	0.11	0.23**	-0.12	-0.10	-0.05	-0.07	0.01	0.19*	0.05	-0.08
7. Public assistance	0.08	0.15*	0.05	0.02	0.19**	-0.10	0.01	0.09	0.08	0.00
8. Recovery	0.00	0.02	-0.10	-0.04	-0.07	0.06	-0.06	0.04	0.04	-0.15*
9. Severity of abnormal movements	-0.05	-0.01	-0.16*	-0.04	0.02	0.00	0.14	-0.03	-0.07	-0.19*
10. Short Physical Performance Battery	0.11	0.04	0.04	0.00	0.00	-0.12	0.00	0.02	0.19*	0.04

Note: *** $p < .001$, ** $p < .01$, * $p < .05$; 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 nveAI, except for Valence for which we used its mean.

Figure 1.

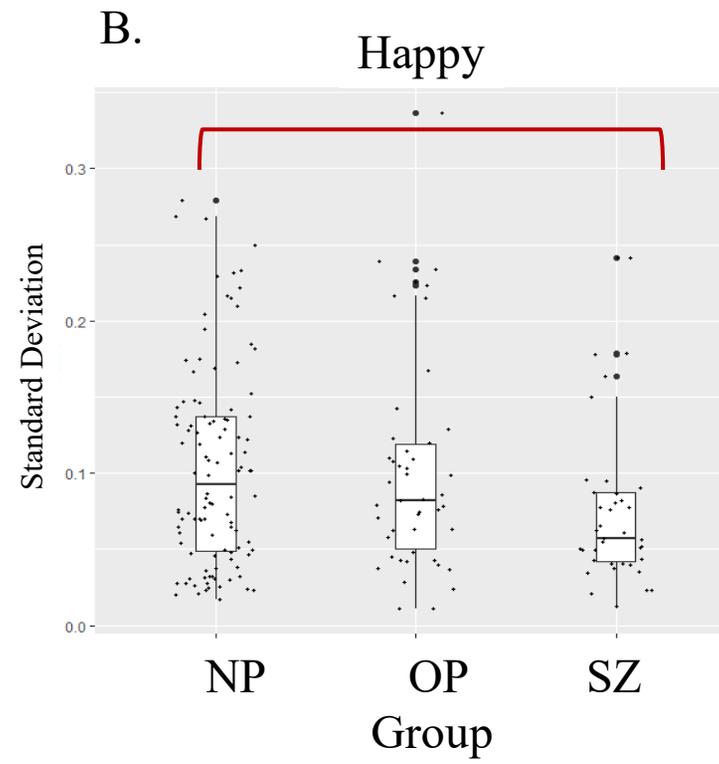
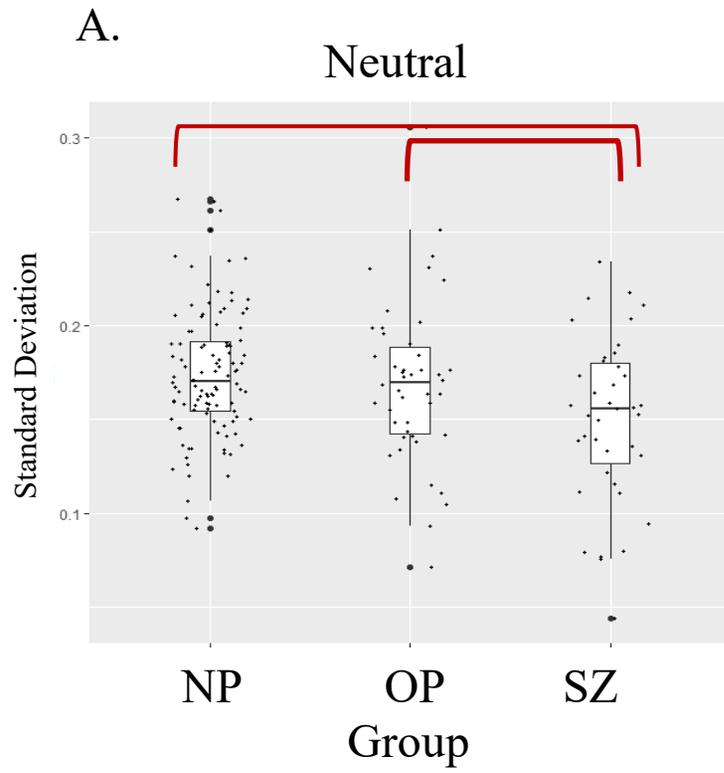


Figure 1 (con't)

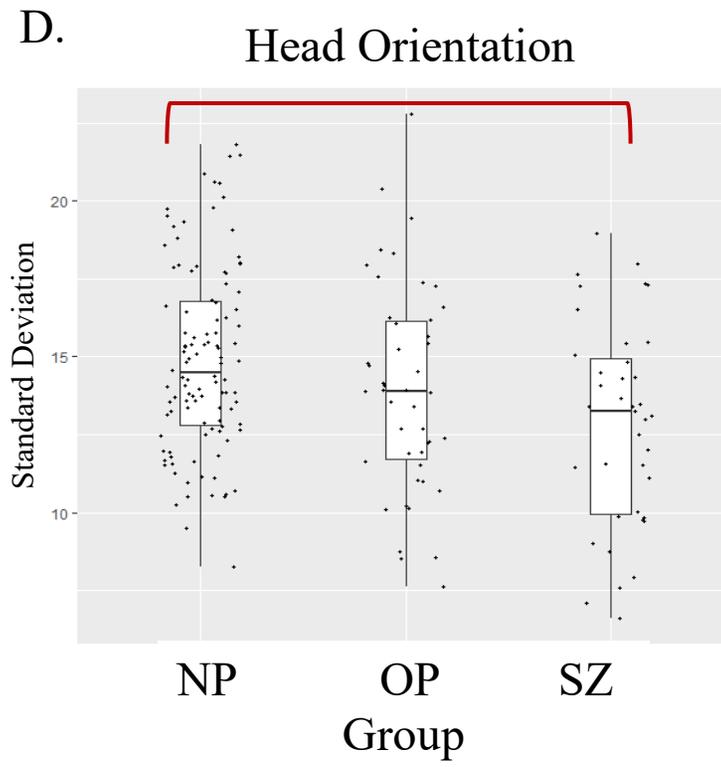
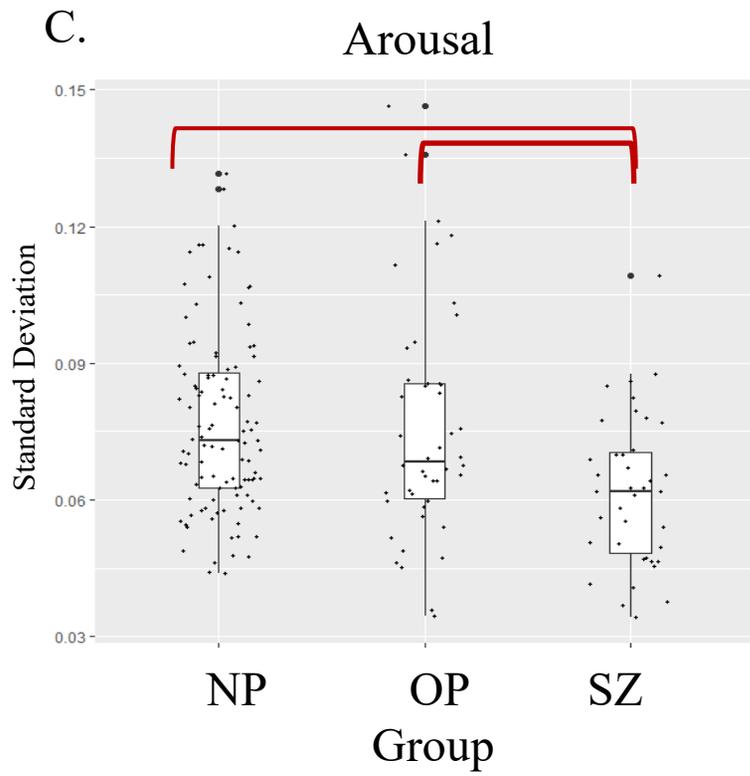
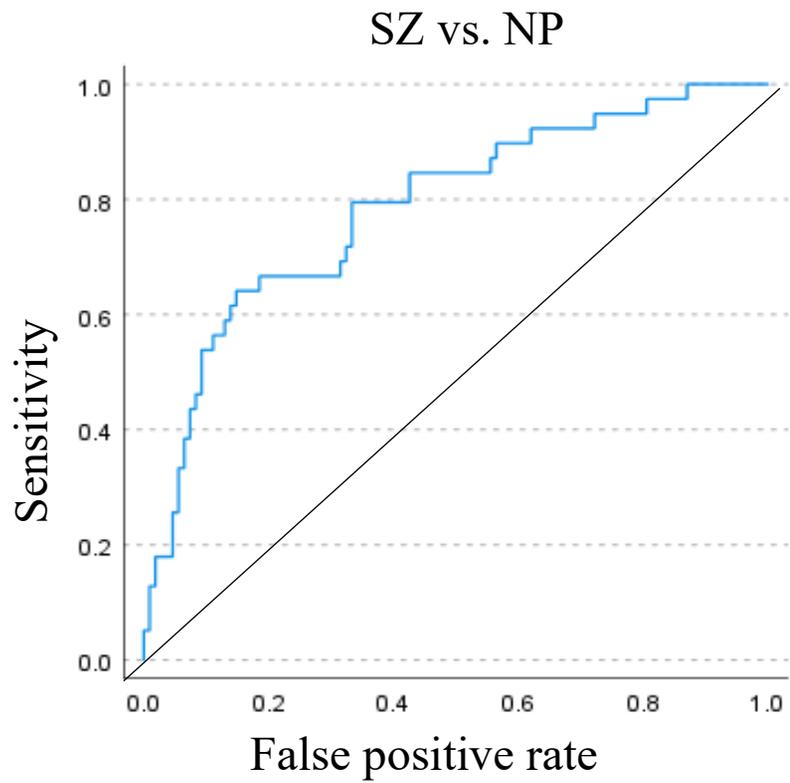


Figure 2.

A.



B.

