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Alterations in Facial Expressions of Emotion: Determining the Promise of Ultrathin Slicing Approaches and Comparing Human and Automated Coding Methods in Psychosis Risk

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Alterations in facial expressions of emotion are a hallmark of psychopathology and may be present before the onset of mental illness. Technological advances have spurred interest in examining alterations based on "thin slices" of behavior using automated approaches. However, questions remain. First, can alterations be detected in ultrathin slices of behavior? Second, how do automated approaches converge with human coding techniques? The present study examined ultrathin (i.e., 1-min) slices of video-recorded clinical interviews of 42 individuals at clinical high risk (CHR) for psychosis and 42 matched controls. Facial expressions of emotion (e.g., joy, anger) were examined using two automated facial analysis programs and coded by trained human raters (using the Expressive Emotional Behavior Coding System). Results showed that ultrathin (i.e., 1-min) slices of behavior were sufficient to reveal alterations in facial expressions of emotion, specifically blunted joy expressions in individuals at CHR (with supplementary analyses probing links with attenuated positive symptoms and functioning). Furthermore, both automated analysis programs converged in the ability to detect blunted joy expressions and were consistent with human coding at the level of both second-by-second and aggregate data. Finally, there were areas of divergence across approaches for other emotional expressions beyond joy. These data suggest that ultrathin slices of behavior can yield clues about emotional dysfunction. Further, automated approaches (which do not require lengthy training and coder time but do lend well to mobile assessment and computational modeling) show promise, but careful evaluation of convergence with human coding is needed.

Keywords: facial expressions, automated coding, thin slicing, clinical high risk for psychosis

Alterations in facial expressions of emotion are a hallmark of psychopathology, including schizophrenia (Andreasen, 1982; Kirkpatrick, Fenton, Carpenter, & Marder, 2006). There is increasing evidence that alterations in facial expressions of emotion are already present prior to the onset of mental illness, including among individuals at clinical high risk (CHR) for psychosis (Gupta, Haase, Strauss, Cohen, & Mittal, 2019). Recent technological advances have led to an upsurge of interest in examining facial expressions of emotion based on "thin slices" of behavior using automated approaches (Cohen, Morrison, & Callaway, 2013; Gupta et al., 2019; Hamm, Kohler, Gur, & Verma, 2011; Lewinski, 2015; Owada et al., 2018). This development has raised important questions.

First, it is unknown whether alterations in facial expressions of emotion can be detected in "ultrathin" (i.e., 1-min) slices of behavior. This is critical because ultrathin slices of behavior (Ambady & Rosenthal, 1992) may be the norm rather than the exception in real-world settings, and their study can provide new insights into emotional functioning in healthy as well as clinical populations and contribute to novel screening and treatment avenues. Second, it is unclear how well automated approaches hold up with gold-standard techniques used to identify facial expressions—specifically, human behavioral coding (Ekman & Friesen, 1978). Despite the growing popularity of automated methods, there is a surprising scarcity of published literature supporting the validity of these approaches. As such, the current study sought to (a) determine alterations in facial expressions of emotion using ultrathin

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(i.e., 1-min) slices of behavior, extending our previous work (Gupta et al., 2019), and (b) determine convergences and divergences between automated and human coding approaches in detecting alterations in facial expressions of emotion in individuals at CHR and matched controls.

Facial Expression of Emotions in Individuals at Clinical High Risk for Psychosis

Facial expressions of emotions have high social visibility (Hager & Ekman, 1979). They play a central role in signaling emotional states to others (Darwin & Prodger, 1998; Schmidt & Cohn, 2001) and in creating and maintaining social relationships (Keltner & Kring, 1998). For example, facial expressions of joy (e.g., upturned mouth, crowfeet around the eyes) can communicate enjoyment (Ekman & Friesen, 1982), create and maintain social bonds, reinforce desired behaviors (Martin, Rychlowska, Wood, & Niedenthal, 2017), and help cope with stress (Bonanno & Keltner, 1997).

Alterations in facial expressions of emotions (e.g., blunted joy expressions) have been documented in disorders such as schizophrenia (Kring & Elis, 2013), and blunting of these communicative signals can impact social relationships (Fervaha, Foussias, Agid, & Remington, 2014). Individuals diagnosed with psychotic disorders such as schizophrenia typically show negative symptoms (i.e., reductions in normal experiences such as motivation and/or goal-directed behaviors). One prominent negative symptom is blunted affect, which captures reductions in facial expressions of emotions (Kirkpatrick et al., 2006). Alterations in facial expressions (i.e., blunted joy expressions) may already be present among individuals at CHR who endorse attenuated positive symptoms (e.g., seeing shadows, hearing whispers; Gupta et al., 2019) and are considered at imminent risk for developing psychosis (Fusar-Poli et al., 2012). In fact, between 10% and 30% of CHR individuals may go on to develop a psychotic disorder such as schizophrenia within a 2-year period (Fusar-Poli et al., 2012).

Measuring Facial Expressions of Emotion

The advent of automated approaches to examine facial expressions of emotion based on thin slices of behavior has gained attention from scientists in numerous fields, including affective, clinical, and computer science (e.g., Hamm et al., 2011; Lewinski, 2015; Owada et al., 2018). Early automated programs were developed (e.g., Littlewort et al., 2011) based on the Facial Action Coding System (FACS), which was created by Paul Ekman and Wallace Friesen (Ekman & Friesen, 1978). FACS is an anatomically based coding system and quantifies facial muscle movements using action units (AUs). For example, AU 6 indicates movement of the orbicularis oculi, pars orbitalis, which raises the cheeks. AU 12 indicates movement of the zygomaticus major, which pulls the lip corners upward. Building on cross-cultural research (Ekman & Friesen, 1971), Ekman and colleagues used specific configurations of facial AUs (e.g., presence of both AU 6 and 12) to determine the presence of specific emotions (i.e., joy, anger, surprise, fear, contempt, disgust, sadness; Ekman, 1992; Keltner, Sauter, Tracy, & Cowen, 2019; Matsumoto, Keltner, Shiota, O'Sullivan, & Frank, 2008). Coding systems that grew out of FACS, such as the Expressive Emotional Behavior (EEB; Gross & Levenson, 1993), quantify these emotion prototypes directly. For example, joy facial behavior would be EEB-coded as 0 if there is no expression, 1 if there is a slight expression such as a slight smile without teeth showing or a half smile, 2 if there is a moderate expression of joy such as a closed-mouth smile, and 3 if there are strong expressions of joy such as cheeks clearly raised and evident wrinkles around the eyes.

FACS and FACS-based coding systems, such as the EEB (Gross & Levenson, 1993) or the Facial Expression Coding System (Kring & Sloan, 1991), were highly influential in pioneering the study of emotion and have been used to assess facial expressions of emotion in individuals with depression, (Archinard, Haynal-Reymond, & Heller, 2000), schizophrenia (Kring & Elis, 2013), and neurodegenerative diseases (Goodkind, Gyurak, McCarthy, Miller, & Levenson, 2010) and among groups from different cultures (Soto, Levenson, & Ebling, 2005). Trained human coders can achieve high reliability in FACS and FACS-based coding systems, such as the EEB (Gross & Levenson, 1993), but this work is very labor and time intensive.

Automated facial analysis tools (e.g., Noldus, 2014; iMotions, 2016) analyze FACS-based AUs derived from prototypical emotion categories (e.g., joy, anger, surprise, fear, contempt, disgust, sadness). These approaches have become quite popular very quickly and have been employed in research studies assessing facial expressions of emotion in individuals with autism spectrum disorder (Owada et al., 2018), depression (Girard, Cohn, Mahoor, Mavadati, & Rosenwald, 2013), schizophrenia (Hamm et al., 2011), and CHR (Gupta et al., 2019). Automated approaches hold tremendous promise for the analysis of facial expressions of emotions because they process high volumes of data at relatively low cost. However, there are important open questions.

Automated tools and human raters often code facial expressions of emotion using a thin slice approach. Thin slices, a term derived from the personality literature, are described as brief segments of time (e.g., less than 5-min) capturing behavioral information such as characteristics, traits, and nonverbal expressions (Ambady & Rosenthal, 1992). Thin slice approaches have been used in a wide variety of studies with healthy and clinical samples, including individuals with psychopathy (Fowler, Lilienfeld, & Patrick, 2009), depression (Sasso & Strunk, 2013), personality disorders (Oltmanns, Friedman, Fiedler, & Turkheimer, 2004), and schizophrenia (Schwartz, Docherty, Najolia, & Cohen, 2019). However, it is unclear how much time is needed to accurately detect clinically relevant alterations. The question as to what is considered an appropriate "slice" for assessing behavioral information has been of interest for decades, but much of this research stems from studies with healthy samples (Carney, Colvin, & Hall, 2007; Hirschmann, Kastner-Koller, Deimann, Schmelzer, & Pietschnig, 2018; James, Wadnerkar, Lam-Cassettari, Kang, & Telling, 2012; Murphy et al., 2015; Tom, Tong, & Hesse, 2010). Of relevance to the present study, it is unclear whether alterations in facial expressions of emotion in individuals at CHR can be detected in ultrathin (1-min) slices of behavior.

Additionally, it is unknown how automated facial analysis tools hold up against each other and human coding approaches. Despite the growing popularity of automated methods to detect facial expressions of emotion, there is a surprising scarcity of published literature supporting the validity of these approaches. In particular, we lack critical knowledge of how different automated approaches

converge or diverge from each other when coding real-world, dynamic facial behavior. Existing comparative studies have relied on static images of (actor-) posed facial expressions using standardized data sets (when the emotion to be detected was "known"; e.g., Revina & Emmanuel, 2018). However, we do not know how different automated approaches perform when it comes to detecting spontaneous facial expressions of human emotion in real-world, dynamic settings (e.g., clinical interviews). Moreover, and perhaps even more critical, it is unclear how automated and human coding of facial expressions of emotion converge. This question is of deep interest to affective and clinical scientists who may wish to determine the validity of automated approaches where algorithms for deriving emotion expressions are often not fully known. At present, there exist only a handful of studies comparing automated and human approaches, all of which (to our knowledge) used exclusively static images from standardized databases and used naïve, untrained human coders (Lewinski, 2015). Finally, it is noteworthy that the development of automated tools relied exclusively on healthy individuals. As we are now starting to use automated approaches in populations with alterations in emotional expression (who may [co-] activate facial muscles differently, which might impact scoring algorithms in unexpected ways), it will be especially important to determine how automated tools perform across clinical groups such as CHR.

The Present Study

In this study, facial expressions of emotions (i.e., joy, anger, surprise, fear, contempt, disgust, sadness) during ultrathin (1-min) slices of video-recorded segments of clinical interviews were analyzed by two automated, computerized facial analysis software tools, and these same segments were rated by two trained human coders. The present study had several noteworthy methodological features in that we (a) examined a CHR group and matched controls (because the early and accurate detection of alterations in facial expressions of emotion in this population is of central importance given the devastating consequences of psychotic disorders; Fervaha et al., 2014), (b) focused on the facial expressions of seven basic emotions (as a first line of inquiry of interest to affective and clinical science research), (c) analyzed spontaneous real-world facial behavior in a clinical interview setting (as a context with high ecological validity), (d) used two widely used, commercially available software packages, and (e) relied on FACS- and EEB-trained human coders who coded facial expressions of emotions on a second-by-second basis using the EEB (as a well-established coding system; Gross & Levenson, 1993).

This proof-of-concept investigation aimed to determine if alterations in facial expressions of emotions in individuals at CHR could be observed in ultrathin (1-min) slices of emotional behavior using automated approaches and human coding. To determine the presence of alterations, we compared a sample of CHR individuals to a healthy matched control group. Furthermore, in order to determine if ultrathin (1-min) slices were picking up on the same alterations detected in thin (5-min) slices, we also took a further step, in a supplementary analysis, to see how strong agreement was between 5-min slices from our earlier study (Gupta et al., 2019). In additional analyses, we determined links between facial expression measures in which group differences were observed in both thin and ultrathin slices of time and (a) positive symptoms (i.e., which are largely central CHR symptoms and include experiences such as unusual thoughts, suspiciousness, and perceptual abnormalities) and (b) global functioning (i.e., overall current functioning in many domains such as psychological, social, and occupational areas of life) in individuals at CHR as two critical markers of psychopathology and functioning in this population (Fusar-Poli et al., 2012; Miller et al., 1999; Yung, Phillips, Yuen, & McGorry, 2004).

Based on prior literature in healthy populations indicating similar findings regardless of slice thickness (Ambady & Rosenthal, 1992; Hirschmann et al., 2018) and patterns detected in our first study (Gupta et al., 2019), we predicted that we would detect alterations in facial expressions of emotion (blunted joy expressions, increased anger expressions) in the CHR group compared to controls using ultrathin slices of behavior and that this would converge with thin (i.e., 5-min) slices. Additionally, we predicted that alterations in facial expressions would be related to higher positive symptom severity and impairments in global functioning. Also, we sought to investigate agreement between automated and human coding approaches in the assessment of facial expressions of emotion within CHR and control groups (focusing on those emotion categories with sufficient variance) by analyzing (a) correlations of composite emotion variables and (b) intraclass correlations (ICCs) based on second-by-second data. To our knowledge, this is the first comparative study of its kind, and we did not formulate a priori hypotheses.

Method

Participants

A total of 84 participants, including 42 CHR individuals and 42 healthy controls (please note that the sample size is in line with our previously published work; Gupta et al., 2019), aged 12–21 years (M = 18.90, SD = 1.91) were recruited through the Adolescent Development and Preventive Treatment Program using several approaches (e.g., Craigslist, flyers). Exclusion criteria consisted of head injury and neurological disorders. The presence of psychotic disorders such as schizophrenia was an exclusion criterion for CHR individuals. Having first-degree relatives with a psychotic disorder was an exclusion criterion for controls. To improve generalizability, CHR individuals were included if they were taking antipsychotic medications. It is important to note this was only applicable for a small subsample (n = 3). The university institutional review board (Protocol 10−0398) approved consent and protocol procedures. Written consent was received by all participants. All participants included in this study consented to being video recorded during clinical interviews.

The Structured Interview for Prodromal Syndromes (SIPS; Miller et al., 2003; Miller et al., 1999) was administered to diagnose a prodromal syndrome and videotaped. CHR participants met SIPS criteria, defined by moderate-to-severe levels of attenuated positive symptoms and/or a decline in functioning (with schizotypal personality disorder or a family history of psychosis).

The SIPS measures *attenuated positive symptom* domains including unusual thought content/delusional ideas (e.g., "Have you ever been confused at times whether something you have experienced is real or imaginary?"), suspiciousness/persecutory ideas (e.g., "Do you ever feel like you are being singled out or

watched?"), grandiose ideas (e.g., "Do you feel as if you are unusually gifted in any particular area?"), perceptual abnormalities/hallucinations (e.g., "Have you ever seen unusual things like flashes, flames, vague figures, shadows, or movement out of the corner of your eye?"), and disorganized communication (e.g., "Do people tell you that they cannot understand you?"). Positive symptom categories are rated from 3 to 5 on a 6-point scale. Examples of anchors for unusual thought content/delusional ideas include unanticipated mental events that are puzzling and not easily ignored (rating of 3); sense that ideas/experiences are coming from outside oneself or that they may be real, doubt remaining intact, experiences that are distracting/bothersome, and experiences that may affect functioning (rating of 4); and experiences that are familiar and anticipated, doubt having to be induced, experiences that are distressingly real, and experiences that affect functioning (rating of 5). The final variable was a total sum score of all attenuated positive symptom domain ratings. Additionally, the SIPS includes the Global Assessment of Functioning (GAF) scale, which was used in this study to measure current *global functioning*. A current rating on a 1–100 scale (1 representing impaired functioning and 100 indicating superior functioning in several activities) is given based off information including psychological health (e.g., depressed mood, anxiety attacks) and social and occupational functioning.

The Structured Clinical Interview for the *DSM–IV* Axis I Disorders (SCID; First, Spitzer, Gibbon, & Williams, 1995) was used to rule out a psychotic disorder diagnosis. Advanced doctoral students were trained on interviews during a 2-month period and were reliable ($\kappa \geq 80$).

Measures

Automated analysis of facial expressions of emotions. The first 1-min of a video-recorded clinical interview was submitted into two automated facial expression analysis tools (iMotions, 2016; Noldus, 2014) to assess seven emotion categories: joy, anger, surprise, fear, contempt, disgust, and sadness. The 5-min video clip data from our prior study (Gupta et al., 2019), which was previously submitted into automated analysis (iMotions, 2016), was used to determine convergence. One software package was iMotions (2016), which uses a commercial automated facial coding tool (Emotient FACET; https://imotions.com) and grew out of the Computer Expression Recognition Toolbox (Littlewort et al., 2011). This software computes *evidence scores* indicating the likelihood (in %) that a specific emotion expression is present based on a predetermined AU-based algorithm. The other software package was FaceReader (Version 7.1), which was developed by Noldus Information Technology. This program also uses predetermined AU-based algorithms and provides a value indicating how much facial activity resembles expressions (e.g., joy). FaceReader values were averaged for each participant, and a percent was computed indicating the likelihood the expression matches a predetermined algorithm (i.e., likelihood an expression is present).

It is important to note that there were no group differences in the ability to register the video recording of participant faces in either program, iMotions: $t(82) = .83$, $p = .41$; FaceReader: $t(82) = .23$, $p = .82$. Over 91% of video frames were recognized by the iMotions (2016) software and over 85% were recognized by FaceReader in this sample at a sampling rate of 30 Hz, suggesting that these videos, on average, were suitable for facial analysis.

Human coding of facial expressions of emotions. Two trained raters coded the same first minute of the video-recorded clinical interviews using the EEB (Gross & Levenson, 1993). Both EEB raters were licensed in FACS, trained in the EEB, and blind to diagnosis. Raters watched each 1-min video segment independently. One rater coded all the videos, with an overlap of 20% coded by the second rater. Interrater reliability was high (ICC = .90). EEB is based on FACS and uses descriptions of specific facial actions to code for the intensity of emotional expressions on a second-by-second basis (i.e., 0 = no expression, 1 = slight, 2 = moderate, 3 = strong). For example, for joy expressions, 0 indicates no visible joy, 1 denotes slight but noticeable joy signaled by a slight smile without teeth showing or a half smile (e.g., cheeks slightly raising and wrinkles appearing around the eyes), 2 describes moderate joy displayed by a closed-mouth smile or a smile with a slight mouth opening (e.g., moderate cheek raise and eye wrinkles), and 3 indicates strong expressions of joy as seen by broad smiles or laughing (cheeks strongly raised and apparent wrinkles around the eyes). Intensity ratings were summed for each emotion. We analyzed the same seven EEB-coded emotion categories as in the automated analysis (i.e., joy, anger, contempt, surprise, disgust, sadness, fear).

Statistical Approach

Analyses using independent *t* tests and chi-square tests were employed to examine differences between groups (CHR and controls) in continuous and categorical demographic variables, respectively. To determine alterations in facial expressions of emotion between CHR and control groups in ultrathin slices of time (1-min), analysis of covariance was used, controlling for depressive symptoms (sum score) obtained from the Beck Depression Inventory (Beck, Steer, Ball, & Ranieri, 1996) to maintain consistency with our prior analyses (Gupta et al., 2019). For the supplementary analysis, bivariate correlations were analyzed to determine relationships between ultrathin (1-min) and thin (5-min) slices for which group differences in facial expressions of emotion were detected. Moreover, to determine links between thin and ultrathin slices from automated analysis and human coding and (a) attenuated positive symptoms and (b) GAF scores, bivariate correlations were applied. To explore agreement between iMotions (2016; automated analysis 1), Noldus FaceReader 6.0 (automated analysis 2), and human coding within CHR and controls, we examined (a) ICCs (based on second-by-second data) across approaches for joy expressions (the emotion category with sufficient variance across approaches) and (b) overall correlations (based on composite data). Planned analyses were corrected for multiple comparisons using a false discovery rate (FDR) correction. A note is made after each set of analyses whether results passed the FDR correction.

Results

Demographics

As shown in Table 1, individuals at CHR did not differ from controls in age, $t(82) = 1.58$, $p = .12$, or parent education, $t(74) = -.44$, $p = .66$, but did differ in biological sex $\chi^2(1) =$

Table 1
Demographic Details

Demographics	CHR	Control	Statistic	*p*
Age *M* (*SD*)	18.90 (1.91)	18.12 (2.61)	$t(82) = 1.58$	.12
Biological sex (counts)			$\chi^2(1) = 5.93$	.02
Male	23	12		
Female	19	30		
Total	42	42		
Parent education (years) *M* (*SD*)	15.51 (2.10)	15.76 (2.89)	$t(74) = -0.44$	.66
Symptoms *M* (*SD*)				
Positive	11.69 (4.70)	0.45 (1.19)	$t(1, 82) = 15$	≤.001
Negative	9.55 (6.84)	0.43 (0.83)	$t(1, 82) = 8.58$	≤.001

Note. CHR = clinical high risk. Parent education is the average of mother and father education. Symptoms are sum scores from the Structured Interview for Prodromal Syndromes.

5.93, $p = .02$. As expected, individuals at CHR endorsed more positive, $t(1,82) = 15$, $p \leq .001$, $d = 3.28$, 95% CI [9.73, 12.75], and negative, $t(1,82) = 8.58$, $p \leq .001$, $d = 1.87$, 95% CI [6.97, 11.26], symptoms compared to controls.

Differences in Facial Expressions of Emotion Derived from Ultrathin Slices of Behavior Between CHR and Control Individuals

Automated analyses. Using automated analysis 1 (see Figure 1), significant group differences were found for joy expressions, $F(1, 74) = 12.25$, $p = .001$, $\eta_p^2 = .14$, such that individuals at CHR displayed lower levels of joy expressions compared to controls. Moreover, significant group differences were found for anger expressions, $F(1, 74) = 4.42$, $p = .039$, $\eta_p^2 = .06$, such that individuals at CHR displayed greater levels of anger expressions compared to controls. No group differences were found for the other emotion expressions, surprise: $F(1, 73) = .04$, $p = .84$; fear: $F(1, 74) = .02$, $p = .88$; contempt: $F(1, 74) = .21$, $p = .65$; disgust: $F(1, 74) = .10$, $p = .75$; sadness: $F(1, 74) = 1.02$, $p = .32$. Findings indicating group differences in joy expressions passed an FDR correction, while group differences in anger expressions did not.

Using automated analysis 2, significant group differences were observed for joy expressions, $F(1, 74) = 11.24$, $p = .001$, $\eta_p^2 = .13$, such that individuals at CHR showed lower levels of joy expressions compared to controls. There were no group differences in the other emotion expressions, anger: $F(1, 74) = 1.38$, $p = .24$; surprise: $F(1, 74) = 2.48$, $p = .12$; fear: $F(1, 74) = .60$, $p = .44$; contempt: $F(1, 74) = 2.51$, $p = .12$; disgust: $F(1, 74) = .06$, $p = .82$; sadness: $F(1, 74) = .35$, $p = .56$. Significant group differences passed an FDR correction. Note that automated analysis 2 also detected expressions of surprise, fear, and sadness, in both CHR and control group, that were different from zero.

Human coding. Using human coding, significant group differences were found for joy expressions, $F(1, 74) = 10.46$, $p = .002$, $\eta_p^2 = .12$, such that individuals at CHR displayed lower levels of joy expressions compared to controls. No group differences were found for the other emotion expressions, anger: $F(1, 74) = .38$, $p = .54$; surprise: $F(1, 74) = .64$, $p = .43$; contempt: $F(1, 74) = .13$, $p = .72$; sadness: $F(1, 73) = .11$, $p = .74$. Please note that fear and disgust are not listed because of lack of variability in data (ratings indicated that these expressions were not present). Significant group differences passed an FDR correction.

Supplementary analysis. In a supplementary analysis, we examined relationships between emotion expressions derived from ultrathin (i.e., 1-min) and thin (i.e., 5-min) slices of behavior in individuals at CHR and controls. We focused on those emotional expressions where we had previously found significant differences between CHR individuals and controls using thin (i.e., 5-min) slices of behavior in analysis 1 (i.e., joy and anger expressions; Gupta et al., 2019). In the CHR group (see Table 2), findings indicated significant associations between ultrathin and thin slices of behavior. Specifically, higher levels of joy expressions observed in thin (i.e., 5-min) slices using automated analysis 1 were correlated with higher levels of joy expressions derived from ultrathin (i.e., 1-min) slices from automated analysis 1, $r = .83$, $p < .001$, automated analysis 2, $r = .73$, $p < .001$, and human coding, $r = .63$, $p < .001$. Additionally, higher levels of anger expressions observed in thin (i.e., 5-min) slices using automated analysis 1 were correlated with higher levels of anger expressions from ultrathin (i.e., 1-min) slices derived from automated analysis 1, $r = .95$, $p < .001$, and automated analysis 2, $r = .48$, $p = .002$, but not human coding, $r = .09$, $p = .58$. In healthy controls (see Table 3), findings for joy expressions were quite similar, whereas findings for anger expressions indicated convergence between thin and ultrathin slices of behavior using automated analysis 1, $r = .73$, $p < .001$, but not automated analysis 2, $r = .13$, $p = .42$, or human coding, $r = .16$, $p = .32$.

In additional supplementary analyses, we determined relationships between thin and ultrathin slices of time (across all facial expression measures) and (a) attenuated positive symptoms and (b) GAF scores. First, lower levels of joy expressions derived from thin (5-min) slices were associated with higher levels of attenuated positive symptoms, $r = -.37$, $p = .015$. Furthermore, when assessing ultrathin slices, lower levels of joy expressions derived from automated analysis 1 were related to marginally higher levels of attenuated positive symptoms, $r = -.28$, $p = .068$. No other significant relationships were observed between joy expressions derived from automated analysis 2, $r = -.19$, $p = .23$, and human coding, $r = -.24$, $p = .12$. Second, in terms of GAF scores, lower levels of joy expressions derived from thin slices, $r = .42$, $p = .006$, and ultrathin slices from automated analysis 1, $r = .33$, $p = .035$,

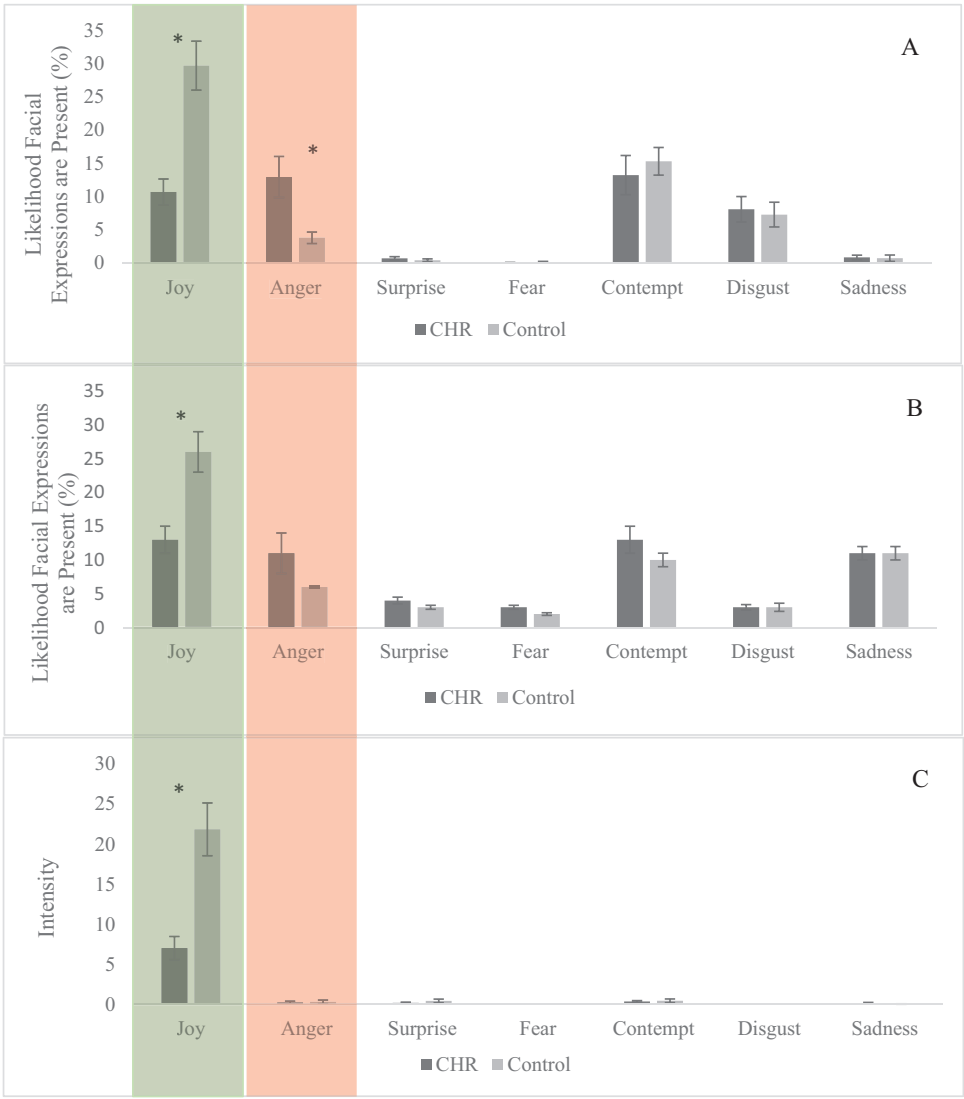

Figure 1. Comparison of (A) automated analysis 1, (B) automated analysis 2, and (C) human coding of facial expression of emotions. The green box indicates methodological overlap in detecting significant group differences in joy expressions. The red box indicates anger was different between groups using automated analysis 1 but not detected with automated analysis 2 and human coders. * $p \leq .05$. Error bars signify standard error. See the online article for the color version of this figure.

and human coding, $r = .38$, $p = .014$, were all significantly associated with lower GAF scores. Moreover, lower levels of joy expressions derived from ultrathin slices from automated analysis 2 were related to marginally lower GAF scores, $r = .30$, $p = .051$.

Associations Between Emotion Expressions Derived from Automated Analysis Versus Human Coding in CHR and Control Individuals

Intraclass correlations for second-by-second emotion expressions across approaches. To determine ICCs for second-by-second emotion expressions across approaches, we focused on joy expressions because all three approaches had detected significant alterations and variation in this emotion variable (base rates for the other emotional expressions derived from human coding were low). In the CHR group, ICCs suggested moderate-to-high levels of convergence between joy expressions derived from (a) automated analysis 1 and 2 (ICC = .76), (b) automated analysis 1 and human coding (ICC = .54), and (c) automated analysis 2 and human coding (ICC = .62). For healthy controls, ICCs suggested high convergence between (a) automated analysis 1 and 2 (ICC = .86), (b) automated analysis 1 and human coding (ICC = .73), and (c) automated analysis 2 and human coding (ICC = .75).

Correlations for overall emotion expressions across approaches. To determine correlations for overall (composite) emotion expressions across approaches, we again focused on joy

Table 2
Correlations Between Thin and Ultrathin Slices of Joy and Anger Expressions Within the Clinical High Risk Group

Ultrathin slices	Joy thin slices	Anger thin slices
Joy automated analysis 1	.83***	−.37*
Joy automated analysis 2	.73***	−.20
Joy human coding	.63***	−.09
Anger automated analysis 1	−.30	.95***
Anger automated analysis 2	−.24	.48*
Anger human coding	−.18	.09

Note. "Thin slices" were obtained from automated analysis 1 from our previous study and refer to 5-minute segments. "Ultrathin slices" refer to 1-minute segments.
* $p < .05$. *** $p < .001$.

expressions derived from human coding (base rates for the other emotional expressions derived from human coding were low). In the CHR group (see Table 4), findings indicated positive, large correlations between overall joy expressions derived from human coding and joy expressions derived from automated analysis 1, $r = .63$, $p < .001$, and 2, $r = .50$, $p = .001$. However, findings also indicated a positive, large correlation between joy expressions derived from human coding and contempt expressions derived from automated analysis 1, $r = .46$, $p = .002$. Remaining correlations were nonsignificant.

For healthy controls (see Table 5), findings indicated positive, large correlations between joy expressions derived from human coding and joy expressions derived from automated analysis 1, $r = .79$, $p < .001$, and 2, $r = .78$, $p < .001$. Moreover, findings indicated negative, moderate-to-large associations between joy expressions derived from human coding and anger expressions derived from automated analysis 1, $r = -.34$, $p = .03$, as well as anger, $r = -.41$, $p = .007$, contempt, $r = -.32$, $p = .04$, and sadness, $r = -.38$, $p = .01$, expressions derived from automated analysis 2. However, findings also indicated a positive, large correlation between joy expressions derived from human coding and disgust expressions derived from automated analysis 1, $r = .42$, $p = .005$. Remaining correlations were nonsignificant.

Discussion

The current proof-of-concept study investigated whether ultrathin (i.e., 1-min) slices of behavior could be used to identify alterations in facial expressions of emotion in individuals at CHR for psychosis. Specifically, we evaluated the convergence and divergence of (a) thin and ultrathin slices and (b) automated and human coding approaches in determining facial expressions of emotions in individuals at CHR and healthy controls. Additionally, we examined links with symptoms and functioning. Findings indicated that ultrathin (i.e., 1-min) slices of behavior were sufficient to reveal blunting in joy expressions in individuals at CHR, which was observed across all methodologies.

Table 3
Correlations Between Thin and Ultrathin Slices of Joy and Anger Expressions Within the Control Group

Ultrathin slices	Joy thin slices	Anger thin slices
Joy automated analysis 1	.90***	−.38*
Joy automated analysis 2	.82***	−.23
Joy human coding	.74***	−.22
Anger automated analysis 1	−.34*	.73***
Anger automated analysis 2	−.38*	.13
Anger human coding	−.04	.16

Note. "Thin slices" were obtained from automated analysis 1 from our previous study and refer to 5-minute segments. "Ultrathin slices" refer to 1-minute segments.
* $p < .05$. *** $p < .001$.

Table 4
Correlations Between Joy Human Coding and Automated Analyses 1 and 2 Within the Clinical High Risk Group

Automated facial analysis tools	Joy human coding
Automated analysis 1	
Joy	.63***
Anger	−.10
Surprise	−.09
Fear	−.05
Contempt	.46**
Disgust	−.08
Sadness	.21
Automated analysis 2	
Joy	.50**
Anger	−.26
Surprise	.09
Fear	−.27
Contempt	.18
Disgust	−.09
Sadness	−.01

Note. In correlational analyses, only joy expressions derived from human coding were assessed due to lack of variability in other human coding expression variables (fear, anger, surprise, contempt, disgust, and sadness).
** $p < .01$. *** $p < .001$.

Table 5
Correlations Between Joy Human Coding and Automated Analyses 1 and 2 Within the Control Group

Automated facial analysis tools	Joy human coding
Automated analysis 1	
Joy	.79***
Anger	−.34*
Surprise	−.23
Fear	.06
Contempt	−.17
Disgust	.42**
Sadness	−.16
Automated analysis 2	
Joy	.78***
Anger	−.41**
Surprise	.14
Fear	−.07
Contempt	−.32*
Disgust	−.01
Sadness	−.38*

Note. In correlational analyses, only joy expressions derived from human coding were assessed due to lack of variability in other human coding expression variables (fear, anger, surprise, contempt, disgust, and sadness).
* $p < .05$. ** $p < .01$. *** $p < .001$.

Moreover, findings showed moderate-to-high (for individuals at CHR) and high (for healthy controls) convergence across automated approaches and human coding in detecting joy expressions using ultrathin slices of behavior. However, divergences across approaches were also observed for some other emotional expressions, emphasizing the need for more research. Additionally, links between thin and ultrathin slices and (a) attenuated positive symptoms and (b) global functioning hint toward the clinical utility of this approach.

Determining the Promise of Ultrathin Slices of Behavior

The present findings showed that ultrathin slices were sufficient to detect blunting in joy expressions in individuals at CHR when compared to healthy controls. Additionally, our supplementary analyses showed that joy expressions detected in ultrathin (i.e., 1-min) slices of behavior were positively correlated with joy expressions detected in thin (i.e., 5-min) slices across approaches. Together, these data provide evidence of blunted joy expressions in individuals at CHR, converging with other findings showing alterations in facial expressions in this group (Evensen et al., 2012; Gur et al., 2006), including our own (Gupta et al., 2019). Given the importance of positive emotional expressions (e.g., smiles) in the creation and maintenance of social relationships (Keltner & Kring, 1998), these findings raise the question of not only whether blunted joy expressions can be used for early prodromal screening but also whether they may play a putative role in the deterioration of social relationships in the prodrome.

There were also discrepancies across methods when determining group differences in other facial expressions. One approach in particular (automated analysis 1) detected heightened levels of anger expressions in individuals at CHR compared to controls. However, these findings were not corroborated by human coding or automated analysis 2 and did not survive FDR corrections. Thus, in this case, the initial discrepancy was resolved when using a more conservative evidence criterion. Similarly, in our previous study in which we also used automated analysis 1 but submitted longer bouts of time for facial expression analysis, CHR individuals were found to display heightened anger expressions. While these findings indicating increased anger expressions from thin and ultrathin slices derived from automated analysis 1 are difficult to interpret, it is possible there may be differences in the way automated analysis 1 specifically is detecting anger expressions compared to other automated and human coding methods.

To further probe clinical utility, we examined relationships between thin and ultrathin slices of facial expressions of emotion and (a) positive symptoms and (b) global functioning (using GAF scores) among individuals at CHR. In terms of positive symptoms, we found links between lower levels of joy expressions (from thin slices) and higher levels of positive symptoms. Furthermore, positive symptoms were marginally associated with ultrathin slices of joy expressions derived from automated analysis 1 but unrelated with automated analysis 2 and human coding. These data suggest that thin slices may be useful in detecting symptomatology, and trend level findings with ultrathin slices also indicate promise. It is important to remember that, like formal psychotic disorders such as schizophrenia, the CHR status itself is in large part defined by the presence of attenuated positive symptoms (Fusar-Poli et al., 2012; Miller et al., 2003), and as such, both thin slice and ultrathin slice methods showed a meaningful link with clinical phenomenology. In terms of global functioning, we found links between lower levels of joy expressions derived from thin and ultrathin slices and impairments in global functioning. These data highlight the possibility that ultrathin slices may be useful in providing clinically meaningful information to identify individuals at CHR who exhibit broad impairment across a variety of domains, including psychological health and different aspects of functioning (e.g., social, role), although, clearly, more work in this area is warranted.

Together, these findings may serve as a foundation for future research investigating the utility of thin and ultrathin slices of behavior (Ambady & Rosenthal, 1993; Oveis, Gruber, Keltner, Stamper, & Boyce, 2009). Such studies may inform not only basic science but also translational application. For example, there may be promise for using facial analysis software in both research and therapeutic settings. To date, the assessment of facial expressions in these environments is often limited to assessor observation, and it may not always be possible to implement manualized coding techniques given that change in symptoms can happen rapidly. Utilizing automated facial analysis tools may provide an efficient way for assessors and clinicians to formulate treatment plans by receiving objective data, allowing for the implementation of appropriate facial expression interventions promptly.

Determining the Promise of Automated Versus Human Coding Approaches

The present study is, to our knowledge, the first to probe the convergence of automated and human coding approaches in detecting facial expressions of emotion using dynamic, real-world video data from individuals at CHR and healthy controls. Overall, findings indicated convergence between joy expressions derived from both automated analysis tools and joy expressions derived from human coding both within the CHR group *and* control group at the level of second-by-second data as well as at the aggregate level.

Our findings indicating that joy expressions from automated analyses were associated with joy expressions from human coding indicate an important area of convergence. At the same time, there were also areas of divergence. For example, joy expressions derived from human coding showed positive associations with contempt (for CHR) and disgust (for control) expressions derived from automated analysis 1 (but not 2) at the aggregate level. It is, of course, possible that joy expressions co-occurred with contempt and disgust expressions. However, our FACS-trained human coders had not picked up on either contempt or disgust, and automated analysis 2 also did not corroborate these findings. These findings not only emphasize the importance of careful assessment of different automated approaches but also highlight the value of human coding in potentially resolving discrepancies between automated approaches. Moreover, results inform methodological questions regarding the efficacy of automated analysis. Automated analysis tools are already being used to examine alterations in

language, motor movements, symptom tracking, digital phenotyping, and more in clinical populations (Dean, Samson, Newberry, & Mittal, 2018; Insel, 2017; Moran, Culbreth, & Barch, 2017; Pennebaker, Booth, & Francis, 2007). Clearly, this is an important area that is ripe for further investigation using dedicated triangulation of different methodological approaches (i.e., different automated approaches, human coding).

Strengths and Limitations

While there are several strengths to the current study such as the novelty of the research question, the multimethod approach, the high ecological validity of the clinical interview setting, and the inclusion of individuals at both CHR and healthy controls, there are, of course, limitations to consider. First, while we assessed the expression of seven basic emotional expressions, in this clinical interview context, meaningful variation was only observed for joy expressions. Future research is needed to examine the usefulness of ultrathin slices and probe convergence across automated and human coding approaches for other key emotions (e.g., anger, sadness, fear), ideally using stimuli designed to elicit these emotions (e.g., film clips, Gross & Levenson, 1995). Second, the present study focused on facial expressions of emotion; future work is needed to examine the convergence of automated and human coding approaches at the level of individual AUs. Third, we assessed facial expressions in the context of clinical interviews, which has several benefits, but additional research should examine facial expressions of emotions in contexts beyond clinical interviews (e.g., dyadic interaction tasks, film clip viewing) in order to understand the generalizability of findings. Fourth, our sample size was small. Even though our sample size is comparable to other studies in this area (e.g., Gupta et al., 2019), our hope is the present work will provide a useful foundation for future, large studies to build on and evaluate the diagnostic potential of ultrathin slices. Additionally, future work could compare longer slices (e.g., 10 min) using automated and human coding approaches, and it could also be advantageous to compare the beginning portions (e.g., first 5-min) to later portions (e.g., last 5 min) of an interview or other experimental task.

Conclusion

Analyzing ultrathin slices of behavior using automated approaches to determine alterations in facial expressions of emotion shows promise—not only for research but also for screening, diagnostics, and treatment of clinical populations, where disease progression can occur rapidly. The present findings indicate that ultrathin (i.e., 1-min) slices can be used to detect blunted joy expressions in individuals at CHR across methodologies, with considerable convergence with gold-standard human coding. At the same time, the discrepancies observed across approaches and the numerous open questions emphasize the need for further research in this rapidly developing area.

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