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Individual Differences in Emotion Prediction and Implications for Social Success

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The social world requires people to predict others' thoughts, feelings, and actions. People who successfully predict others' emotions experience significant social advantages. What makes a person good at predicting emotions? To predict others' future emotional states, a person must know how one emotion transitions to the next. People learn how emotions transition from at least two sources: (a) *internal information*, or one's own emotion experiences, and (b) *external information*, such as the social cues detected in a person's face. Across five studies collected between 2018 and 2020, we find evidence that both sources of information are related to accurate emotion prediction: individuals with atypical personal emotion transitions, difficulty understanding their own emotional experiences, and impaired emotion perception displayed impaired emotion prediction. This ability to predict others' emotions has real-world social implications. Individuals who make accurate emotion predictions have better relationships with their friends and communities and experience less loneliness. In contrast, disruptions in both internal and external information sources explain prediction inaccuracy in individuals with social difficulties, specifically with social communication difficulties common in autism spectrum disorder. These findings provide evidence that successful emotion prediction, which relies on the perception of accurate internal and external data about how emotions transition, may be key to social success.

Keywords: emotion, social cognition, social prediction, social success

Supplemental materials: https://doi.org/10.1037/emo0001386.supp

The social mind is tailored to the problem of predicting other people (Thornton et al., 2019; Thornton & Tamir, 2017). In daily life, successful social interaction requires people to accurately anticipate others' emotions. Knowing that a happy person is likely to stay cheerful while a stressed person is more likely to become irritated than happy allows individuals to avoid social blunders and make socially advantageous decisions. How do people predict others' emotions?

Fortunately for social minds, people display regularity in their emotion dynamics. A previous study that utilized experience-sampling data to examine how individuals' emotions change in real time found reliable patterns in how emotions transition from one to the next (Thornton & Tamir, 2017). For example, people are more likely to transition between similarly valenced emotions like relaxed and happy than between relaxed to grouchy. People also reliably track these real-world emotion transitions, allowing them to accurately predict others' emotion transitions—even when the specific person and timeframe was unspecified. People can use these statistical regularities in emotion transitions, in part, because they are baked into how the brain represents emotions (Thornton et al., 2019). When considering another's current mental state, people's neural patterns more closely resembled states that were likely potential states than unlikely potential states.

Thus, emotion dynamics is a piece of social information that people implicitly learn and can accurately apply when making predictions about others. Emotion prediction is an important social cognitive skill that may aid in successful social functioning.

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However, there is substantial variability in how well people predict the emotions of those around them. Successfully wielding this information can have significant benefits for relationships. Individuals who accurately predict the emotions of their community and friends have better social relationships and well-being (Zhao et al., 2022). Given the observed variability in this ability, what makes a person good at emotion prediction?

The Causes of Accurate Emotion Prediction

People can learn about emotion dynamics through at least two sources. First, people learn about others' emotion experiences by observing others. People gather this *external information* from others' displays of emotion, for example, their facial expressions and body language. Facial expressions provide a wealth of information about other's internal states; though faces can be noisy social cues, people can generally make accurate judgments about another person's current emotional state based on this information (Tracy & Robins, 2008). This ability to perceive emotions from facial expressions should, thus, help people learn how others transition from one emotion to the next. As people perceive others' emotional states over time, they accumulate information about others' emotion dynamics. If people experience disruptions in emotion perception, then their external source of information about emotion dynamics will be inaccurate, leading to inaccurate emotion predictions.

People also learn about emotion dynamics by observing their own emotion experiences. *Internal information*, or information based on one's own experiences and understanding of the world, is a convenient source of information that individuals often use as a starting point for making judgments about others (J. I. Krueger & Chen, 2014). For example, research on perspective taking has shown that people tend to draw upon self-knowledge to make social inferences (Ames, 2004; Dunning & Hayes, 1996; J. Krueger & Clement, 1994; Nickerson, 1999; Ross et al., 1977). People make social inferences by anchoring on self-knowledge and then serially adjusting to account for self–other differences, especially for similar targets (Epley et al., 2004; Tamir & Mitchell, 2013; Todd et al., 2016). Making judgments using this self-projection strategy can be a rational choice in the face of uncertainty about an individual, leading to more accurate inferences and predictions (Dawes, 1989; Hoch, 1987; J. I. Krueger & Chen, 2014; Zhao & Tamir, 2022).

The success of this self-projection strategy depends on at least two factors. First, one's internal experiences must appropriately mirror others' experiences (Hoch, 1987). If a person's emotional experiences and transitions are *typical* or similar to the general population, using internal information should facilitate accurate predictions about others. However, if one's personal emotion transitions are atypical, using the self as a template would result in less accurate predictions, on average. Second, a person must have insight into their own emotion experiences. That is, a person must be able to track the emotions that they experience to know what emotion transitions to project onto others. Emotional self-awareness appears to be a critical component of recognizing and understanding the emotional experiences of others. People with alexithymia, a condition marked by difficulty identifying and describing one's internal emotional experiences, also have difficulty mentalizing about others' feelings (Guttman & Laporte, 2002; Jonason & Krause, 2013; Moriguchi et al., 2006; Swart et al., 2009). If a person's personal experiences are not a good model for others or they are unaware of their own emotional experiences, then their internal source of information about emotion dynamics will be inaccurate, leading to inaccurate emotion predictions.

The Consequences of Inaccurate Emotion Prediction

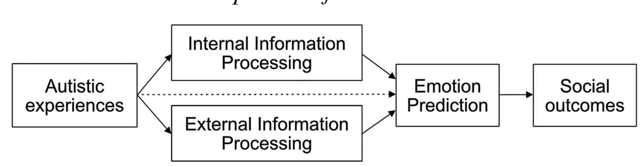
Many clinical disorders are characterized by disruptions in either internal or external affective information. Individuals with autism display difficulties in both domains. Over half of those diagnosed with autism also display alexithymic traits, reporting difficulties understanding and expressing their emotional experiences (Cuve et al., 2022; Hill et al., 2004; Kinnaird et al., 2019; Yu et al., 2022). Challenges with emotion perception are also well-documented in this group, with individuals on the autism spectrum displaying deficits in recognizing others' emotions (Velikonja et al., 2019). Thus, this population experiences distortions in social information inputs—their own and others' emotions—necessary for making accurate inferences and predictions about others.

Individuals who more accurately predict others' emotions enjoy myriad social benefits: lesser loneliness, better friendships, and richer social networks (Zhao et al., 2022). Indeed, in addition to disruptions in both internal and external information sources, autism is characterized by social difficulties. Individuals with autism often report trouble forming and maintaining social relationships, which impacts their daily functioning and quality of life (American Psychiatric Association, 2013; Howlin et al., 2013; Hurlbutt & Chalmers, 2002; Jobe & Williams White, 2007; Kanfiszer et al., 2017; Lin & Huang, 2019; Tobin et al., 2014). Individual interactions require people to accurately anticipate others' future states, and successful relationships develop through such cumulative interactions. Here, we test the hypothesis that inaccurate emotion prediction—rooted in disruptions to both internal and external sources of affective information—underlies difficulties with social interactions (Figure 1).

Overview of Present Studies

Over five studies, we investigated the causes and consequences of accurate emotion prediction. First, we aimed to establish a relationship between emotion prediction accuracy and social functioning outcomes. Next, we examined the relationship between the participants' ability to use two different affective information sources—internal and external—and their emotion prediction accuracy scores. Finally, we examined whether individuals with autistic experiences were less accurate in their emotion predictions

Figure 1
The Causes and Consequences of Emotion Prediction



Note. Many individuals with autistic experiences endorse difficulties with processing internal and external social affective information. We hypothesize that these difficulties lead to less accurate emotion predictions, which in turn affect social functioning.

and whether access to the affective information sources contributed to any observed individual differences.

In addition to investigating these questions using a "generic other" person as the emotion prediction target (Studies 1–5; N = 1,008), we also explored these questions for a person's specific community (Studies 4–5; $N = 462$) and for a specific friend (Study 5; N = 86) to investigate whether (a) the association with social outcomes and (b) the sources of information that individuals utilize differed depending on the social relevance of the target.

Method

Transparency and Openness

All data, code, and materials from this investigation are freely available on the Open Science Framework (https://osf.io/8mtxq/; Barrick et al., 2024). The studies reported in the main article were not preregistered. Data were analyzed using R Studio Version 2021.09.0 (RStudio Team, 2021), and figures were generated in seaborn Version 0.11.2 (Waskom, 2021) using Python Version 3.9.7 (Van Rossum & Drake, 2009). For all studies, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study. All reported results are primary analyses.

Overview

The present investigation included eight separate studies with data collected between 2018 and 2020 that are numbered for clarity and do not indicate chronological order. Studies 1–5 are reported in the main article; Studies 6–8 are reported in the Supplemental Material. Studies 1–5 were parallel behavioral experiments that used similar paradigms to explore (a) emotion prediction accuracy and social outcomes, (b) the social information underlying emotion prediction accuracy, and (c) emotion prediction accuracy in individuals with autistic experiences. Studies 1–5 all investigated these questions for general emotion prediction (i.e., a generic other). Studies 4 and 5 also included emotion prediction accuracy for the participant's local community in an undergraduate population, and Study 5 included emotion prediction for a specific person in the participant's life.

Participants

Participants in Studies 1 ($N = 123$), 2 ($N = 140$), and 3 ($N = 283$) were recruited from Amazon's Mechanical Turk. Study participation was restricted to workers in the United States with >95% approval ratings; participants who had taken part in a study were excluded from subsequent studies. Sample sizes for all studies were determined with a priori power analyses. Effect sizes, targeted effects, and ideal sample sizes for all studies are reported in the Supplemental Table S1. All exclusion criteria were determined a priori. Participants in Study 1 were recruited from a previous study sample that had consented to be recontacted (Supplemental Study S2). Participants in Study 1 were excluded if they completed less than half of the questions ($N = 20$). Participants in Study 2 were excluded if they completed less than half of the questions ($N = 0$) or indicated an English comprehension less than "Good" ($N = 4$). Participants in Study 3 were excluded if they completed less than half of the questions ($N = 0$) or indicated an English comprehension less than "Good" ($N = 1$). Participants in Studies 4 ($N = 376$) and 5 ($N = 86$) were recruited through Sona, a subject pool management system, from the university undergraduate population. Participants in Study 4 were excluded if they completed less than half of the questions ($N = 0$). Participants in these studies represented a diverse sample in terms of age, gender, race, and ethnicity (see Table 1). Participants in all studies provided informed consent in a manner approved by the Princeton University Institutional Review Board. Tasks and surveys for all studies were administered through Qualtrics online survey platform.

Emotion Transitions Task

In the emotion transitions task (Thornton & Tamir, 2017), participants rated the likelihood that a person (generic other, community member, or specific person) would transition between two hypothetical mental states. Prior work established this task as a reliable and externally valid measure of individual differences in emotion prediction. For example, several studies have demonstrated that ratings of emotion transitions on this task accurately match real-world emotion transitions collected in independent samples using experience sampling and real-time reporting. These accurate transition ratings allowed people to predict future emotions approximately two transitions into the future. Accuracy remains high for predicting transitions at both very short as well as longer timescales. Though overall accuracy decreases with increasing intervals, ordinal rank of transition likelihood remains accurate (Thornton & Tamir, 2017). Finally, this measure taps into a meaningful individual difference: it shows high reliability across test–retest (r = 0.63; see Supplemental Material), as well as convergent, discriminant, and incremental validity, with individual differences on emotion prediction correlating significantly with social functioning (Zhao et al., 2022).

On each trial of this task, participants were presented with two mental states connected by an arrow (e.g., happy → angry) and informed that the state to the left of the arrow is the person's current state, and the mental state on the right side of the arrow is a mental state the person might experience next. Participants then rated the likelihood of that person making that transition on a continuous scale from 0% to 100%. Instructions did not include a specific time interval for the mental state transition (see Supplemental Methods for complete instructions).

Participants rated all possible transitions between mental states, including transitions of a state back to itself and transitions in both directions between states. The mental states included in this task contained both cognitive mental states (e.g., "thinking") and affective mental states (e.g., "happy"); however, all states are referred to as "emotions." There are several empirical and theoretical reasons to include both emotional and cognitive states in an investigation of emotion prediction. People use the same processes to predict others future emotional states as they do to predict others' future rational states. Previous work has found that the same brain regions encode both the cognitive and emotional mental states, and both cognitive and emotional states vary on the same psychological dimensions (e.g., valence and social impact vary meaningfully for both cognitive and emotional states; Thornton et al., 2019; Thornton & Tamir, 2020). Cognitive states also appear to be a key-stopping point for people as they transition between negative and positive emotions (Thornton & Tamir, 2017). Emotions also exist on a continuum—people can be experiencing more and less intense

Table 1
Demographic Characteristics

Demographic factor	Study 1	Study 2	Study 3	Study 4	Study 5
N	123	140	283	376	86
M_{age} (SD)	36.94 (9.99)	36.94 (10.75)	37.14 (11.35)	19.43 (1.23)	18.56 (2.08)
Gender					
Female	53 (43.1%)	55 (39.3%)	97 (34.3%)	253 (67.3%)	54 (62.8%)
Male	69 (56.1%)	82 (58.6%)	184 (65.0%)	123 (32.7%)	31 (36.0%)
Other	1 (0.8%)	3 (2.1%)	2 (0.7%)	0	1 (1.2%)
Not stated	0	0	0	6 (1.6%)	0
Ethnicity					
Hispanic/Latinx	13 (10.6%)	16 (11.4%)	68 (24.0%)	45 (12.0%)	19 (22.1%)
Not Hispanic/Latinx	110 (89.4%)	121 (86.4%)	210 (74.2%)	318 (84.6%)	66 (76.7%)
Not stated	0	3 (2.1%)	5 (1.8%)	13 (3.5%)	1 (1.2%)
Race					
American Indian/Alaska Native	2 (1.6%)	0	0	3 (0.8%)	0
Asian	9 (7.3%)	8 (5.7%)	15 (5.3%)	124 (33.0%)	33 (38.4%)
Black/African American	14 (11.4%)	18 (12.8%)	64 (22.6%)	22 (5.85%)	3 (3.5%)
Native Hawaiian/Pacific Islander	0	1 (0.7%)	0	1	1 (1.2%)
White	97 (78.9%)	102 (72.9%)	198 (70.0%)	185 (49.2%)	38 (44.2%)
Other	0	11 (7.9%)	5 (1.8%)	41 (10.9%)	10 (11.6%)
Not stated	1 (0.8%)	0	1 (0.4%)	0	1 (1.2%)

emotions at any one time, and there is no clear line where emotions are "off" and affective processing stops. The current prediction task reflects that people use similar processes along the full emotion continuum, and these processes allow us to accurately predict both emotional and nonemotional states.

Emotions for the pilot study (Supplemental Study S1; angry, anxious, calm, happy, sad, thinking, tired) were chosen from a previous experience sampling study (Thornton & Tamir, 2017) to include states that were clinically relevant to individuals with heightened social impairments. Emotions for Studies 1–4 (irritable, anxious, calm, happy, sad, full of thought, sluggish) were chosen from a previous study (Tamir et al., 2016) as approximate matches for the states used in the pilot study. These matches came with ratings for each state on the psychological dimensions of valence, rationality, and social impact, which were used for additional analyses reported in the Supplemental Results (see emotion representation). Emotions for Study 5 (assertive, confident, grouchy, sad, unrestrained, bold, irritable, lively, nervous, talkative, contempt, disgust, embarrassment, love, satisfaction) were chosen from a previously published study (Zhao et al., 2022). General emotion prediction accuracy was calculated by correlating participant transition ratings with real-world emotion transition likelihoods between the states that were obtained from a previous experience sampling study (Thornton & Tamir, 2017; Trampe et al., 2015; Wilt et al., 2011; see Supplemental Methods for how ground truths were calculated). Community emotion prediction accuracy in Studies 4 and 5 were calculated by correlating participant community transition ratings with the average of the study sample's self-ratings. Friend-specific accuracy for Study 5 was calculated by correlating the participant's ratings of their friend's transitions with that person's self-transition ratings.

Typicality

To assess typicality, we examined how typical each participant's personal transitions were compared to the average person. Participants completed the emotion transitions task, but this time rated the likelihood that they themselves would transition from a hypothetical current emotional state to another hypothetical emotional state, on a continuous scale from 0% to 100%. We assessed the typicality of these personal transitions by correlating them with ratings of personal transitions across a large sample of previous participants from a previous experience sampling study (Thornton & Tamir, 2017).

Emotion Understanding

To measure participants' understanding of their emotions, we administered the Toronto Alexithymia Scale, a 20-item self-report scale that measures difficulty describing feelings, difficulty identifying feelings, and externally oriented thinking (Bagby et al., 1994). Participants answer each item on a 5-point scale anchored at *strongly disagree* to *strongly agree*. Responses were summed to obtain a total score; higher scores indicate more difficulty understanding emotions.

Emotion Perception

To measure emotion perception, we administered the Reading the Mind in the Eyes Task (Baron-Cohen, Wheelwright, Hill, et al., 2001) for Studies 1, 2, and 5. Studies 3 and 4 used the Multiracial version of the Reading the Mind in the Eyes Task, which was developed to reduce the confounding effects of sample characteristics seen in similar tasks by including stimuli depicting various ages, races, and ethnicities and an equal proportion of men and women (Kim et al., 2022). Both the classic and multiracial Reading the Mind in the Eyes Task present participants with pictures depicting the eye region of different faces and instruct them to choose the correct mental state from four listed options. Responses for both tasks were summed to a total score for each participant.

Autistic Traits and Features

The traits and features typically experienced by individuals with autism were assessed using the Autism Quotient (AQ), a 50-item self-report questionnaire designed to measure autistic traits in the general population (Baron-Cohen, Wheelwright, Skinner, et al., 2001). Participants answered each item on a 4-point scale anchored at *definitely disagree* to *definitely agree*. The initial construction of the AQ provided five subscale scores: Social Skills, Attention Switching, Attention to Detail, Communication, and Imagination. Recently, the validity of these subscale constructs has come into question, with multiple studies supporting a three-factor subscale structure over the five-factor structure. Given this recent evidence, the present study reports the AQ results in line with the three-factor structure: (1) Communication/Mind-Reading subscale, which reflects interpersonal abilities during social interactions; (2) Social subscale, which reflects sociability and challenges with specific social skills; and (3) Details/Patterns, which reflects an individuals' propensity to notice patterns and attend to small details around them (English et al., 2020). Participants in all studies completed the Communication/Mind-Reading and Social subscales. Participants in Studies 2–5 also completed the Details/Patterns AQ subscale (see Supplemental Results).

Social Outcomes

Social success was measured using three constructs: loneliness, perceived social support, and social network size. Loneliness was measured using the UCLA Loneliness Scale (Russell, 1996), feelings of social support were measured using the Multidimensional Scale of Perceived Social Support (Zimet et al., 1988), and social network size was measured using the social network nomination (Cohen et al., 1997) and two items from the Social Network Index ("How many close friends do you have?" and "How many of these friends do you see or talk to at least once every 2 weeks?"; see Supplemental Results; Dunbar & Spoors, 1995).

Results

Emotion Prediction and Social Outcomes

The first goal of these studies was to establish the role of accurate emotion prediction in social functioning outcomes. To examine this relationship, we tested the association between emotion prediction accuracy and several measures of social functioning: loneliness, social network size, and perceived social support (see Supplemental Material for complete analyses; see Table 2 for descriptive statistics). We fit separate linear mixed-effects models for each social functioning measure using a restricted maximum likelihood estimation in R (REML; using the *lmer()* function of the lme4 package; Bates et al., 2015; R Core Team, 2021). Initial models consisted of social functioning score separately as the dependent variable (loneliness, social network size, perceived social support), a fixed effect of participants' general emotion prediction accuracy scores, and a random intercept for study to account for study-level variation. p values and standardized coefficients were obtained using the parameters package in R (Lüdecke et al., 2020).

Results revealed that better general emotion prediction accuracy was associated with lower levels of loneliness, $\beta = -.10$, $SE = 0.04$, $t(730) = -2.56$, $p = .01$, larger general social networks, $\beta = .12$, $SE = 0.05$, $t(464) = 2.63$, $p = .01$, and larger networks of close friends, $\beta = .14$, $SE = 0.05$, $t(463) = 3.06$, $p = .002$. General emotion prediction accuracy was not associated with perceived social support, $\beta = .04$, $SE = 0.04$, $t(729) = 1.04$, $p = .30$. These initial results indicated a strong relationship between general emotion prediction accuracy and positive social outcomes.

Table 2
Descriptive Statistics for Study Variables

Variable	*N*	Min.	Max.	*M*	*SD*
Emotion prediction accuracy					
General	1,017	−0.47	0.76	0.38	0.24
Community	469	−0.27	0.94	0.64	0.21
Specific friend	86	−0.23	0.86	0.38	0.28
Typicality	1,017	−0.48	0.74	0.34	0.25
Autism quotient					
Communication/ mind-reading	1,014	7	28	15.41	4.20
Social	1,015	10	52	28.80	8.09
Emotion understanding	1,014	19	85	47.71	14.38
Emotion perception	734	5	35	25.07	5.73
UCLA Loneliness scale	734	20	76	40.50	11.38
Perceived social support	733	12	84	66.192	14.42
Social network nomination					
General network	468	1	95	14.60	11.86
Close network	467	1	36	5.45	3.95

Note. Min. = minimum; Max. = maximum; Emotion understanding = Toronto Alexithymia Scale; Emotion perception = Reading the Mind in the Eyes Task (Studies 1, 2, 5), multicultural Reading the Mind in the Eyes Task (Studies 3, 4); Perceived social support = Multidimensional Scale of Perceived Social Support.

While predicting the average person's emotion transitions has social benefits, people most often interact with close friends and family rather than strangers or hypothetical others. One's ability to tailor emotion predictions to specific people or groups of people may thus be even more impactful for one's social well-being. We next measured emotion prediction accuracy for members of one's local community (Studies 4 and 5) and a specific friend (Study 5) and assessed accuracy for the socially relevant targets and social outcomes.

To test the association between emotion prediction accuracy for one's community and social functioning, we initially fit separate linear mixed-effects models for each social functioning measure, with models consisting of social functioning score separately as the dependent variable (loneliness, social network size, perceived social support), a fixed effect of participants' community emotion prediction accuracy scores, and a random intercept for study to account for study-level variation. Results indicated a singular fit, and subsequent models were simplified to linear models. Using the *lm()* function of the stats package in R, we fit models with each social functioning measure separately as the dependent variable (loneliness, social network size, perceived social support) controlling for study (Studies 4 and 5) to account for study-level variation. Results indicated that better emotion prediction accuracy for one's community was associated with lower levels of loneliness, $\beta = -.21$, $SE = 2.14$, $t(466) = -4.73$, $p < .001$, larger general social networks, $\beta = .14$, $SE = 2.63$, $t(465) = 3.17$, $p = .002$, larger close social networks, $\beta = .14$, $SE = 0.88$, $t(464) = 3.15$, $p = .002$, and higher levels of social support, $\beta = .15$, $SE = 2.69$, $t(465) = 3.37$, $p < .001$.

Next, to test the association between emotion prediction accuracy for a specific friend (Study 5) and social functioning, we fit linear models using the *lm()* function in R, consisting of social functioning score separately as the dependent variable (loneliness, social network size, perceived social support) and participants' friend-specific emotion prediction accuracy scores as the independent variable. Since friend-specific accuracy was only collected in a single study (Study 5), a simple linear model was conducted. Results revealed that better emotion prediction accuracy for a specific friend was associated with lower levels of loneliness, $\beta = -.22$, $SE = 3.76$, $t(84) = -2.02$, $p = .05$, but not general, $\beta = .19$, $SE = 3.55$, $t(83) = 1.77$, $p = .08$, or close social network size, $\beta = .18$, $SE = 1.29$, $t(82) = 1.61$, $p = .11$, or perceived social support, $\beta = .12$, $SE = 5.29$, $t(84) = 1.13$, $p = .26$.

Together, these results provide evidence that the ability to accurately predict others' emotion dynamics is related to socially beneficial outcomes. Accurately predicting others is generally associated with larger social networks and less loneliness, while predicting the people in one's community is associated with larger social networks, less loneliness, and feeling more socially supported. These results replicate previous findings on the link between emotion prediction accuracy for one's local community and specific friends and positive social outcomes (Zhao et al., 2022). If emotion prediction ability contributes to social success, then it is essential to understand what underlies these individual differences in emotion prediction accuracy, namely, which sources of social information that people draw upon when making these emotion predictions support *accurate* prediction?

Information Sources Underlying Accurate Emotion Predictions

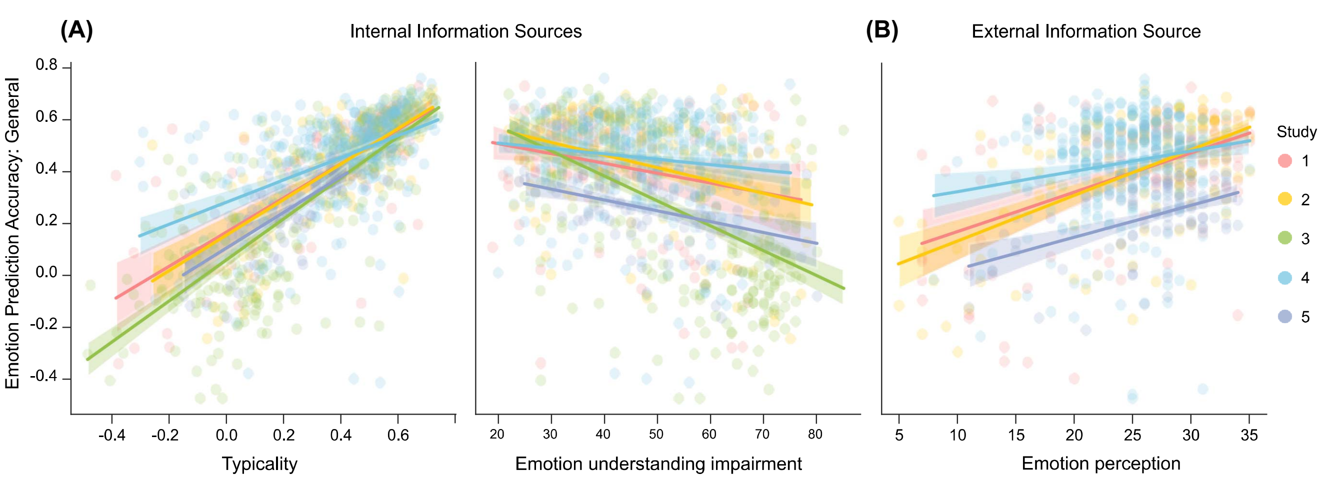
The second goal of these studies was to elucidate the sources of social information that support successful emotion prediction. We tested the association between participant's ability to use internal and external sources of affective information and the accuracy of their emotion predictions. Internal sources were measured by examining participants' *typicality,* or how typical their own emotion transitions are compared to the average person, and *emotion understanding*, or their ability to understand their own emotional experiences using a measure of alexithymia. External sources were measured by examining participants' *emotion perception*, or the ability to judge others' emotions from facial emotion cues. To test the roles of internal and external information in emotion prediction, we fit separate linear mixed effects models for each source of information (typicality, emotion understanding, emotion perception) using a REML in R, using the *lmer()* function of the lme4 package. Initial models consisted of participants' general emotion prediction accuracy scores as the dependent variable, a fixed effect of information source (typicality, emotion understanding, and emotion perception), a random intercept for study to account for study-level variation, and a random slope for each information source. The random slope term was removed to allow the model to converge, so only the random intercept for study was included as a random effect. *p*-values and standardized coefficients were obtained using the parameters package in R (Lüdecke et al., 2020).

Both internal and external sources of information were associated with emotion prediction accuracy (Figure 2). Internal information was associated with better emotion prediction ability, such that individuals with higher emotion prediction accuracy also reported more typical emotion transitions themselves, $\beta = .68$, $SE = 0.02$, $t(1013) = 30.87$, $p < .001$, and a better understanding of their internal emotional experiences, $\beta = -.35$, $SE = 0.03$, $t(1010) = -12.44$, $p < .001$. External information was likewise associated with better emotion prediction accuracy, such that individuals with more accurate emotion predictions also displayed more accurate emotion perception ($\beta = .37$, $SE = 0.03$, $t(730) = 11.38$, $p < .001$).

These results provide evidence that both internal and external information sources are associated with accurate emotion predictions for a generic person. However, we previously found that

Figure 2

Bivariate Correlations Between Emotion Prediction Accuracy and Social Information Sources Within Each Study



Note. Emotion prediction accuracy for a generic other is related to both (A) internal (typicality, emotion understanding impairment) and (B) external (emotion perception) information sources. Results for all studies $p < .001$. Transparent bands reflect 95% confidence intervals. Correlations presented here for visualization purposes; mixed-effects models reported in text are the primary inferential criteria. See the online article for the color version of this figure.

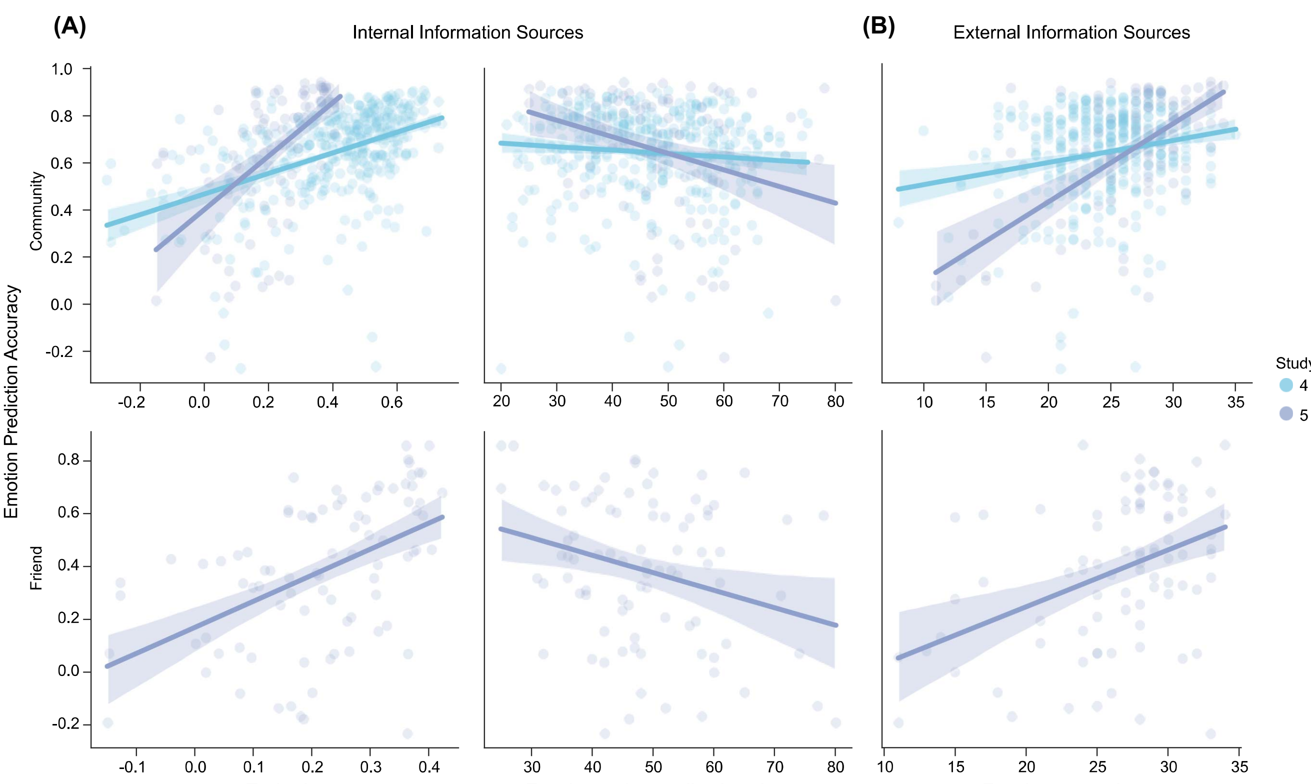
emotion prediction accuracy for both a generic other person and familiar others were related to different social consequences. So, when making emotion predictions about these familiar others, do we draw upon the same sources of information as a generic other? To test this, we initially fit separate linear mixed effects models for each social functioning measure, with models consisted of community emotion prediction accuracy as the dependent variable, each source of affective information (typicality, emotion understanding, emotion perception) separately as independent variables, with a random intercept for study to account for study-level variation. Results indicated a singular fit, and subsequent models were simplified to linear models. Using the *lm()* function of the stats package in R, we predicted community emotion prediction accuracy from each source of information (typicality, emotion understanding, emotion perception) separately, controlling for study (Studies 4 and 5). Next, we fit linear models predicting friend-specific emotion prediction accuracy (Study 5) from each source of information (typicality, emotion understanding, emotion perception), as there was no study-level variation to account for.

Results revealed the same pattern for familiar others as for a generic other (Figure 3). More typical personal emotion transitions were significantly associated with better emotion prediction accuracy for both one's community, $\beta = .49$, $SE = 0.04$, $t(466) = 11.14$, $p < .001$, and specific friend, $\beta = .49$, $SE = 0.19$, $t(84) = 5.13$, $p < .001$. A better understanding of one's internal emotional experiences was significantly associated with better emotion prediction accuracy for both one's community, $\beta = -.14$, $SE = 0.0008$, $t(465) = -3.09$, $p = .002$, and specific friend, $\beta = -.28$, $SE = 0.002$, $t(84) = -2.69$, $p = .009$. Finally, emotion perception was significantly related to accuracy for both community, $\beta = .34$, $SE = 0.002$, $t(466) = 7.71$, $p < .001$, and specific friend, $\beta = .41$, $SE = 0.005$, $t(84) = 4.15$, $p < .001$, such that better ability to distinguish between emotion cues was associated with better emotion prediction accuracy. Together, these results suggest that both internal and external sources of information are related to successful emotion prediction accuracy, both generally and for familiar others. When put in the same model, typicality was the strongest predictor of emotion prediction accuracy (see Supplemental Results for full analysis).

The results thus far indicate that difficulties with affective information processing is associated with worse emotion prediction accuracy, and worse emotion prediction accuracy is associated with worse social outcomes. Although these individual links are robust, unfortunately, a sensitivity analysis indicated that our current data were insufficiently powered to detect the indirect effects of a theoretical model that emotion prediction accuracy mediates the relationship between affective information processing and social outcomes (see Supplemental Results).

Figure 3

Bivariate Correlations Between Emotion Prediction Accuracy and Social Information Sources for Studies 4 and 5



Note. Emotion prediction accuracy for one's community (top row) and a specific friend (bottom row) is related to both (A) internal (typicality, emotion understanding impairment) and (B) external (emotion perception) information sources. Results for all studies $p < .01$. Transparent bands reflect 95% confidence intervals. See the online article for the color version of this figure.

The Causes and Consequences of Inaccurate Emotion Prediction

Accurate emotion prediction has clear social benefits. Could it be that individuals who find social interactions challenging and historically report adverse social outcomes also struggle with making accurate emotion predictions? Here, we explored whether two experiences commonly reported in individuals with autism spectrum disorders, specifically communication difficulties and challenges with social skills, were associated with individual differences in emotion prediction accuracy.

To examine these relationships, we first fit separate linear mixed-effects models for each autistic trait (communication difficulties, social challenges) using an REML in R, using the *lmer()* function of the lme4 package. The models consisted of the participants' general emotion prediction accuracy scores as the dependent variable, a fixed effect of autistic trait (communication difficulties, social skill challenges), and random intercepts for study to account for study-level variation. We also examined whether autistic traits were related to (a) emotion prediction accuracy for one's community by fitting linear models predicting community emotion prediction accuracy from each autistic trait separately, controlling for study (Studies 4 and 5), and (b) emotion prediction accuracy for a specific friend by fitting linear models predicting friend-specific emotion prediction accuracy from each autistic trait (Study 5).

Results revealed that social communication, but not social skills, reliably predicted emotion prediction accuracy. Specifically, individuals with social communication difficulties displayed lower emotion prediction accuracy for generic others, $\beta = -.28$, $SE = 0.03$, $t(1010) = -9.40$, $p < .001$, their community, $\beta = -.16$, $SE = 0.003$, $t(465) = -3.52$, $p < .001$, and a specific friend, $\beta = -.35$, $SE = 0.008$, $t(84) = -3.47$, $p < .001$. Individuals with social skills difficulty showed better emotion prediction accuracy for generic others, $\beta = .07$, $SE = 0.03$, $t(1011) = 2.40$, $p = .02$, but there was no significant relationship between social skills challenges and emotion prediction accuracy for one's community, $\beta = .01$, $SE = 0.001$, $t(466) = -0.75$, $p = .45$, or specific friend, $\beta = -.13$, $SE = 0.005$, $t(84) = -1.16$, $p = .25$. These results suggest that not all individuals who endorse autistic traits may experience emotion prediction difficulties, but rather, those that report difficulty communicating with others experience substantial challenges with emotion prediction. Furthermore, these challenges extend beyond generic emotion prediction to their communities and individual relationships, which may result in negative social consequences.

How do access to internal and external sources of affective information for individuals with communication difficulties contribute to their inaccurate emotion prediction? To examine whether individuals with communication difficulties have disruptions in their social information sources, we fit separate linear mixed-effects models for each source of information (typicality, emotion understanding, emotion perception) using an REML in R, using the *lmer()* function of the lme4 package. The models consisted of information source (typicality, emotion understanding, and emotion perception) as the dependent variable, a fixed effect of communication score, and random intercepts for study to account for study-level variation.

The results provided evidence that both information sources are affected in individuals with heightened communication difficulties. These difficulties were associated with disruptions in internal information sources, such that individuals with more communication difficulties also reported less typical emotion transitions, $\beta = -.21$, $SE = 0.03$, $t(1010) = -6.73$, $p < .001$, and difficulty understanding their internal emotional experiences, $\beta = .65$, $SE = 0.02$, $t(1009) = 26.96$, $p < .001$. Communication difficulties were also associated with worse emotion perception, $\beta = -.32$, $SE. = 0.04$, $t(727) = -8.95$, $p < .001$. These results provide evidence that individuals who struggle with understanding social communication also report difficulty accessing both internal and external information sources of affect information. To what extent do their inaccurate emotion predictions stem from this difficulty?

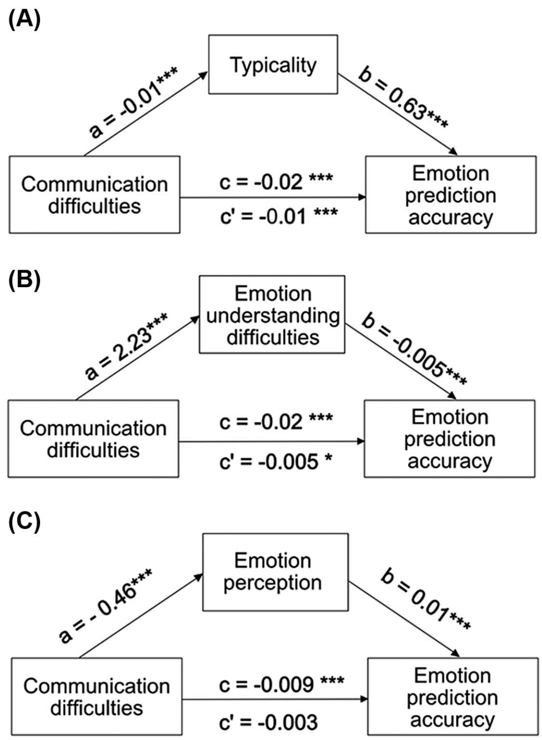
To examine which disruption in social information best explains the relationship between communication difficulties and inaccurate emotion prediction, we conducted three separate multilevel mediation analyses with bootstrapping method (5,000 iterations) using the *mediation* package in R (Tingley et al., 2014). Specifically, we tested how communication skills would predict emotion prediction accuracy via three indirect effects: (a) typicality, (b) emotion understanding, and (c) emotion perception. For each mediation, two multilevel regressions were conducted. The first regression model included each information source (typicality, emotion understanding, emotion perception) separately as a dependent variable, communication skills as the independent variable, with study as random intercept. The second regression model included emotion prediction accuracy as the dependent variable, communication skills, and each information source (typicality, emotion understanding, emotion perception) separately as independent variables, with study as random intercept.

Results (Figure 4) indicated that both internal and external information sources mediated the relationship between social impairments and emotion prediction accuracy. Typicality partially mediated the relation between communication skills and emotion prediction, as the indirect pathway was significant ($b = -0.008$, 95% CI [−0.01, −0.006]), and the direct effect of communication skills on emotion prediction remained significant when typicality was included in the model ($b = -0.008$, 95% CI [−0.01, −0.006]). Emotion understanding also partially mediated the effect between communication skills and emotion prediction (indirect effect: $b = -0.01$, 95% CI [−0.01, −0.008]; direct effect: $b = -0.005$, 95% CI [−0.009, −0.0008]). Emotion perception fully mediated the effect between communication skills and emotion prediction accuracy, as the direct effect of communication skills on emotion prediction accuracy ($b = -0.003$, 95% CI [−0.007, 0.0002]) was no longer significant with emotion perception in the model, while the indirect pathway remained significant ($b = -0.006$, 95% CI [−0.007, −0.004]). Additionally, the three mediators were weakly correlated (typicality, emotion understanding: $r = -.29$, $p < .001$; typicality, emotion perception: $r = .29$, $p < .001$; emotion understanding, emotion perception: $r = -.34$, $p < .001$). These results suggest that in individuals with heightened communication difficulties, difficulty understanding emotions in themselves and reading emotions in others contributes to their emotions prediction challenges.

Discussion

Successful navigation of the social world requires people to make accurate predictions about others. However, previous studies have shown that individuals vary in how accurately they can predict others' emotions (Thornton & Tamir, 2017; Zhao et al., 2022). What underlies these individual differences in emotion prediction accuracy? Five studies assessed potential causes and consequences

Figure 4
Mediation Models of Communication Difficulties on Emotion Prediction Accuracy Through Social Information Sources



Note. Mediation diagrams: a, b, c, and c' are path coefficients representing unstandardized regression weights. The c path coefficient represents the total effect of communication difficulties on general emotion prediction accuracy. The c' path coefficient refers to the direct effect of communication difficulties on emotion prediction accuracy. Typicality (A) and emotion understanding (B) difficulties partially mediate the effects of communication difficulties on emotion prediction accuracy. Emotion perception (C) fully mediates the relationship between communication difficulties and emotion prediction accuracy.
* $p < .05$. *** $p < .001$.

of emotion prediction accuracy. Here, we show that people with better emotion prediction accuracy—for a specific target, a generic target, or one's local community—all predict better social functioning. We then show that people with better emotion prediction accuracy may do so by drawing upon accurate internal and external emotion information sources. People made more accurate emotion predictions if they experienced typical emotion transitions, could understand their own emotion experiences, and could accurately perceive others' emotional expressions. However, these information sources were less accessible to individuals who reported difficulties with social communication, which may explain why challenges with social communication abilities impair emotion prediction accuracy.

Here, we found a significant association between positive social outcomes and emotion prediction accuracy for three targets—close friends, their local community, and people in general. Specifically, people that accurately predict people in general have larger social networks and lower loneliness; people that accurately predict socially familiar others report larger social networks, less loneliness, and higher feelings of social support. Making accurate social predictions may confer social advantages because they allow individuals to more effectively plan their actions based on another's current state to maximize positive outcomes and avoid faux pas. For example, one might choose to bring a stressed roommate a cup of tea and wait until they are feeling calmer to admonish them for leaving dishes in the sink. Making these types of calculated social decisions should minimize negative social interactions and maximize the types of interactions that foster closeness and social support. That said, the cross-sectional nature of these studies does not allow us to draw causal conclusions about this relationship. Do people with fewer social relations have fewer opportunities to learn about others' emotion transitions? Or do people with difficulties making emotion predictions find it hard to create new social connections? We hope that future work might build on our current findings to lend insight into the potential causal direction of this relationship.

People make less accurate emotion predictions if they have difficulty using internal sources of information about emotion transitions. There is robust evidence that people use self-knowledge when making inferences about others (Epley et al., 2004; Todd et al., 2016; Tamir & Mitchell, 2013). Consistent with this, our findings show that people use their own emotion transitions to make predictions about others' transitions. This strategy fails, however, when one's personal transitions are atypical. That is, individuals with emotion transitions that were different than most people were less accurate at predicting the emotion transitions of others. This aligns with prior work on the dialectical misattunement hypothesis and theory of double empathy, which suggest that people with different experiences will have difficulty interacting with and empathizing with each other (Bolis et al., 2018; Milton, 2012). If individuals with atypical experiences cannot rely on their own self-knowledge as a source of social knowledge, they may have fewer opportunities to feel connected with others and to help others feel understood and connected to them.

People likewise will make less accurate emotion predictions if they have difficulty using external sources of information about emotion transitions. People learn about emotion transitions, in part, by observing the emotion experiences of those around them. The process of tracking others' emotion dynamics requires identifying their current emotional state, recognizing when that state changes, and identifying their new emotional state. If people are unable to perceive others' emotions because they cannot infer emotions from facial expressions, vocal tone, or emotional language, then this disrupts the process of learning emotion dynamics. Without the ability to build a model for how emotions transition from one to the next (Thornton et al., 2023), people cannot make accurate emotion predictions. Our findings support this idea, showing that individuals with difficulty perceiving emotions from others' facial expressions make more inaccurate emotion predictions. If individuals struggle with using external sources of social information when interacting with others, they may misinterpret social cues and make poor social decisions, resulting in negative consequences for their social relationships.

The results here indicate that both internal and external affective information are important for making accurate emotion prediction; however, some additional analyses suggest that the information sources we draw from may shift depending on the target (see Supplemental Results). For individuals we are less familiar with, we appear to draw mostly from our self-knowledge of how emotions should transition. However, as we become more familiar with the target, we may rely more on other sources of information such as external cues to make our judgements. Future work should investigate the relative importance of different information sources for different target populations.

These findings have direct applications to clinical populations. People with difficulty communicating with others also displayed less typical emotion transitions, more difficulty understanding their emotional experiences, and impaired facial emotion perception, which was associated with lower emotion prediction accuracy. Difficulty understanding social cues and employing socially normative behaviors are challenges frequently reported by people with autism and have been linked to difficulty forming and maintaining relationships (Howlin et al., 2013; Hurlbutt & Chalmers, 2002; Jobe & Williams White, 2007; Kanfiszer et al., 2017; Lin & Huang, 2019; Tobin et al., 2014). Research aimed at alleviating social difficulties often focuses on improving access to reliable external sources of social information. Social skills groups and technology-based interventions aim to teach social expectations, conversational cues, and recognition of facial expressions. We suspect that the mild to moderate efficacy of these strategies could be enhanced by adopting several additional strategies for intervention (Ke et al., 2018): teaching an understanding of one's own emotion experiences and/or teaching the transition likelihoods for the general population. Recent research has indicated an important role for alexithymia in social outcomes for individuals with autism (Oakley et al., 2022; Scheerer et al., 2021; Vaiouli & Panayiotou, 2021). Despite the evidence for the role of emotion understanding in social functioning for this population, few interventions have aimed to target this specific difficulty. Given our current findings that individuals with communication difficulties endorse alexithymia, which in turn is associated with worse emotion prediction and social outcomes, new interventions focusing on amplifying access to internal information sources may be a fruitful avenue. In addition, teaching transition likelihoods may enhance prediction accuracy. In an additional study, we found that individuals with heightened autistic traits were able to effectively learn the statistical probabilities between mental state transitions (see an additional study in Supplemental Material). Interventions that combine strategies to enhance the understanding of internal experiences and emotion dynamics could be particularly effective in individuals with social functioning difficulties, where an improvement in emotion prediction accuracy may have a cascading effect on social functioning outcomes.

Though our findings suggest that certain autistic experiences are related to emotion prediction accuracy, it is important to note that these studies examined autistic experiences in a nonclinical population. Future work should extend these findings by testing emotion prediction accuracy in clinical populations known to experience social difficulties, such as individuals diagnosed with autism spectrum disorder or schizophrenia spectrum disorders. Additionally, our samples and ground truth measures were restricted to individuals that primarily speak English and resided in the United States at the time of participation; thus, the results may only be generalized in a Western cultural context. Future studies may want to explore demographics and cultural variations in emotion transitions and the roles that typicality, emotion concept, and perceptual cues play in emotion prediction.

Constraints on Generality

The samples in our studies were collected through online platforms and from undergraduates at a U.S. university. Though the full sample was relatively diverse with respect to gender, age, ethnicity, and race, they were obtained through convenience sampling methods and thus may not be fully representative of the general population. Additionally, we were unable to examine other demographic factors in this sample, such as level of education and socioeconomic status, and thus are unable to speak to their possible influences on emotion prediction. We also examined autistic experiences using a self-report measure in community samples and therefore do not have information on whether any individuals in the study have received a diagnosis of autism spectrum disorder. Given this limitation, it is possible that the results may not generalize to individuals with full-threshold clinical disorders.

It is also important to note that the task used to assess emotion perception focused specifically on the eye region of the face. The face conveys important social information about an individual's internal state (Bar et al., 2006; Guarnera et al., 2015; Martinez et al., 2016; Serrano et al., 1992), and laboratory tests of emotion perception predict social outcomes in real-world settings (Hess et al., 2016). However, emotion perception does not happen in a vacuum. Emotion judgements can be highly sensitive to contextual information from body language and gestures, tone of voice, cultural background, and situational variables (Cowen et al., 2021; Le Mau et al., 2021; Reschke & Walle, 2021). Any of these variables, in concert with a facial expression, may alter the perceiver's judgment of the emotion compared to facial expression alone. It is possible that the controlled nature of the emotion perception task used in this study may not generalize to individual's emotion perception ability during real-world social interactions. Future studies should explore the relationship between emotion prediction accuracy and emotion perception by using naturalistic and dynamic tasks and following the recommendations suggested in a review article by Barrett et al. (2019).

Conclusion

Predicting the emotions of others is a key component of social interaction. Our findings suggest that one's ability to accurately engage in this process may have consequences for social well-being and relationships. Disruptions in internal emotional experiences and difficulty recognizing emotion in oneself and others contribute to emotion prediction inaccuracy and help explain the low emotion prediction accuracy displayed by individuals with social difficulties. These findings help illuminate individual differences in how people successfully or unsuccessfully navigate the social world.

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