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Accurate Emotion Prediction in Dyads and Groups and Its Potential Social Benefits

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Abstract

Emotion dynamics vary considerably from individual to individual and from group to group. Successful social interactions require people to track this moving target in order to anticipate the thoughts, feelings, and actions of others. In two studies, we test whether people track others' emotional idiosyncrasies to make accurate, target-specific emotion predictions. In both studies, participants predicted the emotion transitions of a specific target — either a close friend (Study 1) or a first-year college roommate (Study 2) — as well as an average group member. Results demonstrate that people can make highly accurate predictions both for specific individuals and specific groups. Accurate predictions rely on target-specific knowledge; new community members were able to make accurate predictions at zero-acquaintance, but accuracy increased over time as individuals accrued specialized knowledge. Results also suggest that accurate emotion prediction is associated with social success in both individual and communal relationships and that such a relation might emerge over time. Overall, our studies suggest that people accurately make individualized predictions of others' emotion transitions and that doing so fulfills a meaningful function in the social world.

Keywords

emotion; social prediction; social cognition; close relationships; social success

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Prediction is central to social cognition. Whether in cooperation or competition, social interactions require people to anticipate others' future thoughts, feelings, and actions and prepare their own actions accordingly (Tamir & Thornton, 2018). The ability to intuit another person's social future should confer immense social advantage, as it should aid action planning and thus facilitate smoother social interactions. Yet predicting the future feelings of any specific individual is a challenging task. Emotion dynamics vary considerably from individual to individual and from group to group. The same rainy weather might lead to lasting feelings of negativity (and damp socks) for a colleague who tends to wallow, but only fleeting annoyance for one who is more optimistic. To truly reap the social benefits afforded by accurate social prediction, people must tailor their predictions to the

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target they are predicting. To what extent do people tune into these idiosyncrasies to predict how others' emotions evolve over time? In the current study, we investigate the hypotheses that people can accurately predict specific individuals' future emotions and that accurate social prediction provides real world social benefits.

Predicting Emotion Transitions

Emotions are not isolated events occurring in a vacuum (Barrett, 2017). Instead, a person's state at any given moment depends on how their previous states unfold over time. State transitions can take place through multiple potential pathways. Some take place due to internal causes, as people actively regulate their emotions and shift into a different state (Gross, 2002). Other state transitions occur because new external events take place, and how these new events lead to internal experiences will be conditioned on the previous state (Rinck, Glowalla, & Schneider, 1992). Marginalizing over these different mediating factors, emotion dynamics often follow predictable patterns (Cunningham, Dunfield, & Stillman, 2013), so people can use what they know about how other people feel in the moment to predict how they might feel in the future. Someone who is currently feeling anxious is more likely to become frustrated next rather than joyous, whereas someone who is currently feeling hopeful is more likely to feel joyous next rather than frustrated. People can learn how emotions evolve over time by experiencing these regularities in their own emotional lives and by observing these regularities in others. People can then leverage knowledge about these regularities to form accurate predictions about others' future states. Previous research has found that people are indeed highly accurate when they are asked to predict how a general target transitions from state to state (Thornton & Tamir, 2017). That is, people's predictions about the average person mirror the ground truth about how emotion transitions occur in the population.

In everyday life, people need to make predictions about specific individuals, rather than a general target. While emotion dynamics follow predictable patterns in general, individuals vary greatly in both how strongly and how frequently their emotional states fluctuate (Kuppens, Oravecz, & Tuerlinckx, 2010). These individual differences in emotion dynamics are robust and stable (Davidson, 2004; Heller et al., 2015). Thus, in order to make accurate person-specific predictions, it is unlikely that people indiscriminately apply their general understanding of emotion transitions to an individual. A complete model of social prediction must explain how people make predictions about the emotion transitions of specific individuals.

People likely constrain their predictions by drawing on relevant knowledge. Prior research has shown that people make social inferences by drawing on different sources of knowledge depending on the features of the target. For example, people are more likely to draw on knowledge about themselves to make inferences about similar others and stereotypes for dissimilar targets (Ames, 2004; Tamir & Mitchell, 2013). People also fine tune their social inferences based on familiarity with target individuals (Welborn & Lieberman, 2015). Friends are more accurate than randomly paired strangers at inferring each other's thoughts and feelings. This is not because they are more similar but because they have superior individualized knowledge about each other (Stinson & Ickes, 1992). Having specialized knowledge about a target thus increases one's inferential and empathic accuracy.

In the current study, our primary goal is to answer two questions about social predictions in the domain of emotions. First, we test whether people can make accurate predictions about specific individuals, such as a friend or a new roommate. We do so by comparing person-specific predictions against the target's self-reported emotion transitions. In prior work, self-reported emotion transitions correlated strongly with ground truth transition probability (Thornton & Tamir, 2017). This indicates that they are a reasonable choice against which to benchmark others' predictions. Second, we test whether people make accurate predictions by invoking person-specific knowledge and not simply their understanding of general emotion dynamics, nor knowledge about their own emotion dynamics.

Social Perception and Its Benefits

People's mental states — their thoughts, feelings, beliefs, and emotions — shape how people behave. An angry person is more likely to aggress than a happy person. Thus, being able to perceive others' current states should help perceivers to gain strategic command over their own social surrounding. Indeed, people seem highly adept at inferring others' unobservable inner worlds. This mind-reading feat has been a central fascination in social psychology and has been broadly studied across various literatures such as empathy (Decety & Jackson, 2004), emotion recognition (Martinez, Falvello, Aviezer, & Todorov, 2016), empathic accuracy (Ickes, 1993), and theory of mind (Gopnik & Wellman, 2012; Gordon, 1986). These literatures indicate that people can indeed accurately perceive others' mental states (Ickes, Stinson, Bissonnette, & Garcia, 1990; Zaki & Ochsner, 2011). This coincides with findings from the person perception literature showing that people form accurate impressions of others' personality traits (Funder, 1995).

Social perception research also indicates that the ability to accurately infer others' ongoing mental experiences is associated with positive real-world social outcomes. Children who can more accurately track the beliefs and intentions of multiple agents enjoy greater acceptance from their peers (Banerjee, Watling, & Caputi, 2011). Adolescents who can more accurately infer the specific contents of others' ongoing thoughts and feelings enjoy better general social adjustment and greater peer acceptance (Gleason, Jensen-Campbell, & Ickes, 2009); adults who do so enjoy greater satisfaction in romantic relationships (Sened et al., 2017). Thus, there is a clear link between social perception and social success.

However, our social world requires that people go beyond reactive inferences about others' ongoing or past emotions. Much like in a game of chess, where seeing multiple steps into the future enables strategic planning, gazing into others' emotional futures would allow people to project their own courses of action further in time. People who can anticipate others' emotions before they occur should benefit from an even greater strategic command over their social surroundings. Such predictions are intertwined with perception in that people might be able to foretell others' future emotions using perceivable information about their ongoing ones.

The Benefits of Social Prediction

We suggest that social prediction should be a powerful driver of social success. Naturalistic social interactions require people to make continuous, rapid social inferences as they unfold in real time. Yet time pressure often undermines people's social inferences (Epley, 2004; Gershman, Gerstenberg, Baker, & Cushman, 2016). While people are adept at rapidly forming impressions (Ambady, 2010; Willis & Todorov, 2006) and perceiving emotions (Martinez et al., 2016) from observation, social prediction can serve as an additional mechanism for offloading such pressure. Anticipating others' thoughts and feelings a few steps ahead can prime people for interactions well before they take place, and knowledge of emotion transitions should allow people to do precisely this. That is, one's ability to use the knowledge they have in the moment to make accurate predictions about the future should be an important springboard for social success in at least two ways.

First, accurate social predictions should help people form stronger relationships with individual friends. As relationships develop, people have repeated opportunities to interact with each other. To the extent that people can learn their friends' idiosyncratic emotional experiences and learn to accurately predict how they might think or feel, they should be able to have higher-quality interactions at each turn and therefore enjoy more successful relationships. Here we test whether people who can make more accurate prediction about a friend's emotion transitions also enjoy more success in their relationship.

Second, accurate social predictions should help people interact more successfully with their local community. While well-known others and close friends constitute a large part of people's social environment, people's daily social interactions are not restricted to these individuals. People's social success also depends on the success of their interactions within the broader social milieu. Groups exhibit idiosyncratic norms around emotions; they can vary widely in how members should emotionally respond to different events, how emotions should be displayed, and which emotions they value (Kolb, 2014). For example, American cultures value high-arousal states and low-arousal states similarly, whereas East Asian cultures value low-arousal states more than high-arousal ones (Tsai, 2007). Group members actively maintain their group membership by feeling and displaying the "correct" emotions (Kolb, 2014; Mesquita, Boiger, & De Leersnyder, 2016). In order to make accurate predictions about unfamiliar group members, people must learn and then take into consideration the emotional norms and dynamics of their communities. If one's group-level understanding is closely tuned to the regularities of their social group, they could accurately predict others' emotion transitions, even at zero acquaintance. This would facilitate smooth initial interactions and downstream friendship formation. Here we first test whether people can make accurate predictions of emotion transitions for their current social community; we next test whether people who are more accurate about their group's emotion dynamics enjoy more general social success.

Social perception and social prediction likely both contribute to social success. However, the two might contribute for different reasons. Perceiving emotions in the moment requires that people translate between observed expressions and unobservable mental states, a skill that may rely on using either theory-like knowledge (Skerry & Saxe, 2015) or first-person simulation (Waytz & Mitchell, 2011) and depends on both context and culture (Barrett, Mesquita, & Gendron, 2011; Gendron, Roberson, van der Vyver, & Barrett, 2014). Predicting how emotions change over time requires that people not only perceive other's current emotion but also track the emotion dynamics of their social milieu, a skill that might rely on statistical learning (Newport & Aslin, 2004). Here we use a conventional measure, the Reading the Mind in the Eyes Test (RMET; Baron-Cohen, Jolliffe, Mortimore, & Robertson, 1997), to test to what extent emotion perception ability might align with emotion prediction ability. We also test whether perception and prediction differentially predict social success.

The Current Study

In two studies, we examine social predictions in the domain of emotions and mental states within the context of a local university community. In both studies, participants predict emotion transitions for three different targets: their study partner, the average student at their university, and themselves. In our primary analyses, we test whether people make accurate person-specific predictions using tailored person-specific knowledge. Next, we test whether people make accurate group-level predictions. Finally, we test whether individual and group-level accuracies are associated with relationship success and general social success, respectively.

In Study 1, we recruited a sample of close friends who had lived in the same community for at least a semester. We aimed to establish that people can make specific and accurate predictions about their longstanding friends and established community groups. These data also provide a first test of whether the accuracy of one's emotion predictions is associated with any metrics of social success. In Study 2, we recruited a sample of newly acquainted roommates. These data thus allow us to examine the speed with which people can learn to generate accurate predictions as well as the extent to which social benefits of accurate predictions emerge over time. We expected that new dyads would successfully predict the emotions of their partner and their community, though to a lesser extent than established dyads. Further, we expected that the relation between accuracy and social success will not yet have emerged at the very early stage of relationship.

Study 1

Method

Code and data availability.—Data and code from this study have been deposited on the Open Science Framework (https://osf.io/fmkj7/) and are freely available. We report how we determined sample size, all data exclusions, all manipulations, and all measures in the study. All null hypothesis significance tests are two-tailed.

Participants.—Forty-seven same-sex dyads (N = 94, 72 women and 22 men) who identified each other as close friends were recruited through SONA, a subject pool management system, from the Princeton University undergraduate population (M_{age} = 19.68, SD = 1.60; 50% White, 29.8% Asian, 12.8% Black or African American, 5% more than one race, and 2% unreported; 15.8% Hispanic or Latino). A target sample size of 43 dyads was set a priori; a power analysis based on prior research showed that this sample size would provide 95% power to detect the expected accuracy of participants' emotion predictions (d = 0.39; Thornton & Tamir, 2017). The current sample exceeded the a priori criterion set by this power analysis to allow for the exclusion of participants who did not complete the study as instructed. Due to technical difficulties, 3 dyads did not complete the Reading the Mind in the Eyes Test. These dyads were excluded from analyses involving the RMET. One participant provided predictions for the group with zero variance. This participant was excluded from all analyses that include group-level predictions. No data exclusion occurred otherwise. All participants in this and all subsequent studies provided informed consent in a manner approved by the Princeton University Institutional Review Board.

Emotion transition task.—Dyads arrived at the laboratory together but were tested separately. Participants first completed the emotion transition task. In this task, participants judged how likely it was that one state (e.g., happiness) would transition into another state (e.g., elation) for a particular target. On each trial, participants saw a target (e.g., self) and pair of emotional states (e.g., happiness → elation). Participants used a continuous scale from 0% to 100% to rate the likelihood that, if the target were currently experiencing the first state, they would next experience the second state. The states used in this task consisted of three independent sets of five emotional states. To select these states, we applied k-medoids clustering to three large sets of transitional probability data from previous research (Thornton & Tamir, 2017). The state at the center of each cluster was chosen. This selection process ensured that the emotional states used in our task spanned the state space, such that results would not be limited to certain subregions of the space (see Table 1). Stimuli consisted of all possible state pairs within each set (See online supplemental materials for details on state selection). Participants completed a total of 75 trials. Trials were randomized within target blocks.

Each participant completed the emotion transition task three times, providing transition ratings for three targets: (a) self ratings, a participant's ratings of their own emotion transitions; (b) friend ratings, a participant's ratings of their friend's emotion transitions; and (c) group ratings, a participant's ratings of the emotion transitions of the average student at their university. The three targets were presented in blocks in random order across participants.

The dyadic design allowed us to assess the ground truth of actual friend and group transitions, respectively: (a) friend-actual, a participant's friend's self-reported ratings of their own emotion transitions, and (b) group-actual, the sample's average self-ratings, calculated separately for each participant to exclude themselves and their friend.

We tested whether people could make accurate person-specific predictions in three ways. First, we calculated bivariate correlations between participants' predictions for their friend (friend ratings) and the actual transitions provided by their friend (friend-actual). These correlation coefficients were then Fisher's z-transformed and subjected to a one-sample t test. Following previous research, we benchmarked our labels for accuracy against Cohen's convention for effect size (Jussim, Crawford, & Rubinstein, 2015). We report raw correlations greater than .4 as accurate, those between .25 and .4 as moderately accurate, and those below .25 as inaccurate.

Second, to investigate whether participants are specifically accurate about their friend, we iteratively permuted participants' dyad assignments. In each iteration, we calculated bivariate correlations between participants' predictions and the actual transitions of their randomly assigned "partner". These correlation coefficients were then Fisher's z-transformed, and their mean was taken. Across 10,000 iterations, we obtained an empirical sampling distribution of mean mismatched person-specific accuracy. If participants' predictions were specifically accurate for their friend, the correctly matched mean accuracy from analysis one should occupy a high percentile when compared against the mis-matched accuracy distribution. Finally, we tested whether people make person-specific predictions by invoking person-specific knowledge or by drawing up either their understanding of general emotion dynamics or knowledge about their own emotion dynamics. To tease apart these sources of knowledge, we used linear mixed effect modeling and model comparison to examine the independent contribution of each of the three ratings (i.e. friend ratings, group ratings, and self ratings) in predicting friend-actual. The linear mixed effect models were implemented through the lme4 package in R (R Core Team, 2018). If participants use person knowledge to tune their predictions of emotion transitions, friend ratings should predict friend-actual even after controlling for self ratings and group ratings.

We investigated group-level accuracy in two ways. First, to test how accurately participants can predict an average group member's emotion transitions, we calculated bivariate correlations between the participants' predictions for the group (group ratings) to predict the group's actual average self ratings (group-actual). These correlation coefficients were then Fisher's z-transformed and subjected to a one-sample *t* test. Second, to tease apart the sources of knowledge that people use to make group-level predictions, we used linear mixed effect modeling and model comparison to examine the independent contribution of group ratings and self ratings in predicting group-actual. If participants use group knowledge to tune their predictions of emotion transitions, group ratings should predict group-actual even after controlling for self ratings.

Social success measures.—Participants completed measures of two types of social success, general social success and relationship success. General social success was assessed with validated measures of social network size and social support and loneliness (the UCLA loneliness scale; Russell, 1996). Both the size of one's social network (Campbell, Marsden, & Hurlbert, 1986) and one's feeling of loneliness (Gow, Pattie, Whiteman, Whalley, & Deary, 2007) have been used to index how well an individual fares in the general social arena. Relationship success was measured with the Respondent Affection subscale of the McGill Friendship Questionnaire (MFQ; Mendelson & Aboud, 1999) and self-reported closeness. The MFQ is an empirically validated measure of positive feelings in friendships and has been widely used as a measure of relationship quality (Buote et al., 2007; Mendelson & Kay, 2003). Self-reported closeness is a face valid measure of the subjective sense of interpersonal closeness in a friendship and has also used in social psychology (Bahns, Crandall, Gillath, & Preacher, 2017) and neuroscience (Welborn & Lieberman, 2015).

To test whether accurate predictions about a friend relate to relationship success, we assessed the relation between participants' person-specific accuracy and their friend's responses on the relationship success measures. To test whether accurate predictions about the group relate to general social functioning, we assessed the relation between participants' group-level accuracy and their own responses on the general social success measures. These analyses were conducted using bivariate Pearson correlations, bootstrapped to obtain 95% confidence intervals for these correlation coefficients.

In addition, participants completed the RMET to measure social perceptive ability. The RMET served as a reference point for the validity of person-specific and group-level accuracies as predictors of social success. We assessed the RMET's relation with measures of both friendship and general social success, as well as both measures of predictive accuracy. Participants completed the social success measures in random order.

Finally, we collected data on participating dyads' friendship duration and assessed whether it was associated with person-specific accuracy.

Results

Person-specific accuracy.—Our primary analyses investigated whether participants could accurately predict the self-reported emotion transitions of a specific target, namely their friend in the current study. To do so, we first calculated the bivariate correlation between friend ratings and friend-actual for each participant. These correlation coefficients were r-to-z transformed and subjected to a one-sample t test. The mean r-to-z transformed correlation was significantly above zero ($M = 0.68$, average $r = 0.57$, CI [0.62 0.73], $d = 2.54$), suggesting that participants were indeed able to accurately predict their friends' emotion transitions (see Figure 1).

Second, we tested whether participants' predictions are specifically accurate for their individual target. To do so, we conducted a permutation test where we calculated how accurate participants' predictions would have been for randomly selected individuals other than their target. We then compared actual accuracy scores against the distribution of these mismatched accuracies. Correctly matched accuracy was significantly greater than chance ($p = .0056$; Figure 2), indicating that participants' person-specific predictions are not only accurate, but also specific to their target (see online supplemental materials for a conceptually similar analysis).

Third, we examined the extent to which people drew upon person-specific knowledge to accurately predict a friend's emotion transitions. Specifically, we sought to distinguish the contributions of three sources of information to participants' predictions: person-specific knowledge, self-knowledge, and group-level understanding. These contributions were operationalized as the contribution of friend ratings, self ratings, and group ratings, respectively, in predicting friend-actual.

Friend-actual was included as the dependent variable; friend ratings, self ratings, and group ratings were included as predictors. Random intercepts were included for both subjects, nested in dyads, and for items (emotion pairs). The three predictors included in this model were highly correlated with each other. Self ratings and friend ratings had a correlation of $r = .70$; group ratings and friend ratings had a correlation of $r = .71$; and self ratings and group ratings had a correlation of $r = .73$. Thus, the extent to which Friend ratings predicts Friend-Actual in this model reflects how well individuals are able to go beyond their group-level understanding and self-knowledge and use person-specific knowledge to predict a specific target's emotion transitions.

As expected, results of a linear mixed-effects model showed that participants used tailored, person-specific knowledge about their friend to make their accurate predictions: Friend ratings significantly predicted friend-actual ($b = 0.07$, $\beta = 0.07$, $t(6887) = 5.60$, $p < .001$); there was no significant relation between friend-actual and group ratings ($b = -0.02$, $\beta = -0.02$, $t(6932) = -1.52$, $p = .13$) or self ratings ($b = 0.01$, $\beta = 0.01$, $t(6920) = 0.49$, $p = .63$). Thus, in spite of a high degree of shared variance, friend ratings made significant independent contribution to predicting friend-actual over and above the contribution of group ratings and self ratings. That is, even though participants made largely similar emotion transition predictions for themselves, their group, and their friend, they nevertheless fine-tuned their predictions about their friend using person-specific knowledge.

To further assess the independent contribution of person-specific knowledge to predictive accuracy, we compared the full model above to two reduced models. These model comparisons tested whether friend ratings was a better predictor of friend-actual than self ratings and group ratings. The first reduced model used self ratings and group ratings (but not friend ratings) to predict friend-actual. The full model performed significantly better than this reduced model ($BIC_{full} = 62{,}890$, $BIC_{reduced} = 62{,}913$, $\chi^2 = 31.22$, $p < .001$), indicating that the inclusion of participant's person-specific ratings allowed the model to fit the data significantly better. We also compared the full model to a second reduced model using only friend ratings to predict friend-actual. Results showed that the full model, including self ratings and group ratings, did not perform significantly better than the model with friend ratings alone ($BIC_{reduced} = 62{,}875$, $\chi^2 = 2.27$, $p = .32$). These results corroborated the findings from the analyses above and further confirmed our hypothesis that individual possess the ability to utilize individualized information to accurately predict the emotion transitions of specific individuals.

These multiple regression analyses shared similarities with componential approaches to modeling interpersonal accuracy (Furr, 2008). In a componential approach, interpersonal accuracy is modeled as a combination of different accuracy components. One example is the Social Accuracy Model (Biesanz, 2010), where accuracy is jointly determined by components such as normative accuracy, how much one's impressions of others correspond to the characteristics of an average person, and distinctive accuracy, how well one perceives a target's unique characteristics. Analyses conducted in line with the SAM approach replicate results from the multiple regression analysis, showing a significant relation between friend ratings and friend-actual after controlling for self ratings and group ratings (see online supplemental materials for details).

Additionally, we found that person-specific accuracy was correlated with friendship duration ($r(92) = 0.16$, CI [0.003, 0.32]), suggesting that either accuracy promotes durable friendships, or that people learn to become more and more accurate over the course of a friendship.

Group-level accuracy.—Next, we investigated whether individuals could accurately predict the emotion transitions of the average group member (group-actual) using analyses parallel to the person-specific analyses above. First, we calculated the bivariate correlations between group ratings and group-actual for each participant. These correlation coefficients were r-to-z transformed and subjected to a one sample t test. The mean r-to-z transformed correlation was significantly above zero ($M = 1.12$, average $r = .78$, CI [1.05, 1.18], $d = 3.41$; Figure 1), suggesting that participants accurately retain the aggregate pattern of emotion transitions in their community. This replicated and extended the findings that people can accurately predict population-level transitions (Thornton & Tamir, 2017), here within a personally relevant social group.

Second, we examined the independent contribution of participants' group-level understanding in predicting the aggregate-level emotion transition patterns. We conducted this analysis using a linear mixed effect model. In this model, we investigated the relation between group ratings and group-actual while controlling for self ratings. Group-actual and self ratings were included as predictors whereas group ratings was included as the outcome variable. Random intercepts were included for participants, nested within dyads, and for items. There was a significant relation between group ratings and group-actual after controlling for self ratings ($b = 0.63$, $\beta = 0.49$, $t(143) = 33.71$, $p < .001$). These results suggest that participants did not simply use their self-knowledge to make predictions about the average group member. Rather, participants have knowledge about the group-level regularities in emotion transitions that contributed independently group-level accuracy.

Social success.—To the extent that predicting others' emotions facilitates social interactions, people who can predict emotion transitions with greater accuracy should enjoy greater social success. First, we tested the extent to which person-specific accuracy correlated with two measures of relationship success (see Table 2). Participants' person-specific accuracy correlated with their friends' score on the Respondent Affection scale ($r(92) = 0.15$, CI [0.01, 0.30]). The correlation between participants' person-specific accuracy and their friend's perceived closeness was likewise positive but not statistically significant ($r(92) = 0.12$, CI [−0.04, 0.25]). Note that the current sample showed a ceiling effect on the Respondent Affect Scale, with a mean of 2.96 and a median of 3 on a scale ranging from −4 to 4 (see Table S1 for means and standard deviations of all social success measures). As such, correlational analyses involving the Respondent Affection scale should be considered with this compression of range in mind. Together, these results suggest that the more accurately a person can predict their friends' emotions, the more successful their friendship.

Next, we tested the extent to which group-level accuracy correlated with general social success (see Table 2). As expected, participants' group-level accuracy was negatively correlated with loneliness ($r(91) = -0.28$, CI [−0.45, −0.10]). That is, the more accurately a person can predict their community's emotions, the less lonely they feel. Group-level accuracy was negatively, though not significantly, correlated with participants' social network size ($r(91) = -0.15$, CI [−0.35, 0.05]) and uncorrelated with participants' support network size ($r(91) = 0.05$, CI [−0.15, 0.25]). Together, these results provide preliminary evidence that the more accurately a person can predict their group's emotion transitions, the more fulfillment they find in their immediate social environment, though this was not reflected in the quantity of social connections.

Finally, we tested the relation between a traditional measure of social–cognitive ability, the RMET, and each measure of social success (see Table 2). This serves a reference point for the convergent and discriminant validities of person-specific and group-level accuracies. Participants' RMET was positively associated with their friends' perceived closeness ($r(86) = 0.21$, CI [0.03, 0.38]); RMET was not correlated with any other measure of friendship or general social success (see Table 2). RMET was also uncorrelated with person-specific accuracy ($r(86) = 0.08$, CI [−0.12, 0.28]) and group-level accuracy ($r(86) = 0.09$, CI [−0.08, 0.28]). In contrast, person-specific and group-level accuracy were significantly correlated ($r(85) = 0.50$, CI [0.34, 0.65]) suggesting common learning or inferential processes might underlie both. Together, these results suggest that the accurate prediction of emotion transitions may be a construct independent from social perceptive ability as measured by the RMET.

Study 2

Study 1 demonstrated that people can specifically and accurately predict the emotion transitions of particular individuals and social groups. Moreover, prediction accuracy was associated with both their relationship success and their general social success. In Study 2, we aimed to extend these findings beyond the context of highly familiar individuals and social groups and investigate emotion predictions in a sample of newly acquainted dyads: first-year college roommates. Study 2 was the first time point of an ongoing longitudinal study. Longitudinal analyses were preregistered but do not make up part of the current investigation.

Unlike established close friends, first-year college roommates do not yet have significant stores of knowledge about each other. Studying this population allows us to measure emotion prediction among individuals with smaller stores of specialized knowledge. Thus, we can assess how quickly people learn the specialized knowledge necessary to make accurate predictions. By the same token, a first-year college student sample would allow us to investigate the accuracy of group-level predictions in members that are newly introduced to the group, as well as how quickly people can learn to make more accurate group-specific predictions.

In the current study, we make several predictions. First, we predict that the sample of new students tested in Study 2 should be able to capitalize on general regularities in emotion transitions and achieve accurate predictions both for their new acquaintance and for their social group. However, we also predict that they should be less accurate than the sample of close friends tested in Study 1, as these students had had more time to develop specialized knowledge about their partner and their social group. We will capitalize on variance in the date of participation across our sample to test for the development of knowledge over time.

We expect that the more time that a member of this current sample has spent with their new acquaintance and social group, the more accurately they should be able to predict that acquaintance and social group.

Finally, we test for the relation between predictive accuracy and social success. We expect that this relation emerges slowly over time, as a result of repeated interactions. Recently acquainted dyads and community members should not yet have reaped the benefits that accurate predictions confer on social success. Thus, we do not expect to see a correlation between new students' person-specific accuracy and relationship success, nor between group-level accuracy and general social success.

Method

Participants.—Participants were first-year undergraduate students at Princeton University. Each student signed up together with one roommate. Fifty-nine newly formed roommate dyads completed the study (N = 118, 88 women; M_age = 18.44, SD = 1.65; 46.6% White, 33.9% Asian, 7.6% Black or African American, 8.5% more than one race, 1.7% others, 0.8% Alaskan Native and American Indian, and 0.8% unreported; 9.3% Hispanic or Latino). Participants were recruited at the very beginning of the school year, within six weeks of the first day of the semester. All students successfully completed in that time frame (M = 24 days; range = 0–40 days). All roommates were assigned by university housing rather than self-selected. Participants knew each other for 26.7 days on average (range = 0–83 days). One dyad was excluded from analyses due to prior acquaintanceship (relationship duration = 345 days). No other dyads in the sample were prior acquaintances. Data for Study 2 were collected as the first wave of a longitudinal project. A sample size of 40 dyads was set for the longitudinal study. Fifty-nine dyads were recruited for the first wave to allow for potential attrition.

Emotion transition task.—The emotion transition task and the accuracy measures obtained from the task were identical to those used in Study 1.

Social success measures.—Participants completed measures of both relationship success and general social success. Relationship success was measured using the Reis-Shaver Intimacy Index (Reis & Shaver, 1988), the Respondent Affection subscale of the McGill Friendship Questionnaire (Mendelson & Aboud, 1999), and subjective ratings of closeness and liking used in Study 1. We tested the relation between participants' person-specific accuracy and their roommate's responses on the relationship success measures. General social success was measured using the Social Network Index, the UCLA loneliness scale, and network nomination measures used in Study 1. We tested the relation between participants group-level accuracy and their own responses on the general social success measures. All relations were tested using the same procedure as Study 1.

Finally, participants completed the RMET. The RMET was used to test the convergent and discriminant validities of both person-specific and group-level prediction accuracy measures. We assessed the RMET's relation with relationship and general social success, as well as both measures of predictive accuracy. Participants completed all measures in random order.

Results

Person-specific accuracy.—We investigated whether participants could accurately predict their roommate's self-reported emotion transitions in three analyses. First, we calculated the bivariate correlation between friend ratings and friend-actual for each participant. These correlation coefficients were then subjected to a one-sample *t* test after r-to-z transformation. The mean r-to-z transformed correlation was significantly above zero ($M = 0.51$, average $r = 0.44$, CI [0.46 0.57], $d = 1.69$), evidencing that members of newly formed dyads can already accurately predict their target's specific patterns of emotion transitions (see Figure 2). However, this accuracy is significantly lower than that observed in established close friends dyads in Study 1, $F(1, 208) = 17.99$, $p < .0001$.

Second, we tested whether participants' predictions were specifically accurate to their individual target. We iteratively permuted participants' dyad assignment to obtain an empirical sampling distribution of mismatched accuracy. Correctly matched accuracy was significantly greater than chance ($p = .0016$; Figure 4), indicating new college roommates can already make person-specific predictions.

Third, we assessed the contribution of person-specific knowledge in accurately predicting specific targets' emotion transitions, using the same analysis as in Study 1, with a linear mixed effect model predicting target's self ratings with a participants' friend ratings, self ratings, and group ratings. Results indicated that tailored person knowledge contributed to accurate person-specific predictions. Friend ratings significantly predicted friend-actual after controlling for self ratings and group ratings ($b = 0.05$, $\beta = 0.05$, $t(8654) = 4.54$, $p < .001$). Neither group ratings ($b = 0.01$, $\beta = 0.01$, $t(8633) = 0.85$, $p = .40$) nor self ratings ($b = 0.02$, $\beta = 0.02$, $t(8655) = 1.31$, $p = .19$) significantly predicted friend-actual in this model. Consistent with results from Study 1, participants made similar predictions of emotion transitions for themselves, their group, and their friend. Self ratings and friend ratings had a correlation of $r = .62$, group ratings and friend ratings had a correlation of $r = .64$, and self ratings and group ratings had a correlation of $r = .68$. Nonetheless, friend ratings made significant independent contribution to predicting friend-actual, indicating that even participants in new relationships fine-tuned their person-specific predictions using individualized knowledge.

To further validate the results of the linear mixed effects model, we tested whether friend ratings better predicted friend-actual than self ratings and group ratings did. We did so by comparing the full model above to two reduced linear mixed effect models. The first reduced model used self ratings and group ratings (but not friend ratings to predict friend-actual). The full model performed significantly better than this reduced model ($BIC_{full} = 78{,}435$, $BIC_{reduced} = 78{,}446$, $\chi^2 = 20.54$, $p < .001$). This indicates that including person-specific ratings allowed the model to fit the data significantly better. The second reduced model used only friend ratings to predict friend-actual. The full model, even though including self ratings and group ratings as additional predictors, did not significantly outperform this second reduced model ($BIC_{full} = 78{,}435$, $BIC_{reduced} = 78{,}420$, $\chi^2 = 3.51$, $p = .17$). Model comparison results corroborated our hypothesis that accurate person-specific predictions are made by incorporating individualized knowledge about the target person.

The results thus far suggest that participants are able make accurate and specific predictions about a new roommate within only a few weeks of acquaintance. Thus, we next assessed whether people accumulate this person-specific knowledge over time. That is, we tested the bivariate correlation between person-specific accuracy and relationship duration. Participants' person-specific accuracy for their roommate was significantly correlated with the number of days since they first met when the study was completed ($r(114) = 0.23$, CI [0.07, 0.37]). Even at a very early stage of relationship, dyads that have known each other longer can more accurately predict each other's emotion transitions. Since relationship duration cannot be a product of predictive accuracy in new roommates, this result potentially suggests that people can rapidly acquire information that is needed to accurately predict specific individuals' emotion transition. To estimate participants' accuracy at zero acquaintance, we conducted an exploratory linear model equivalent to this bivariate test, using relationship duration to predict person-specific accuracy. This model had an estimated intercept of .38. That is, at zero acquaintance, people can already somewhat accurately predict their roommate's emotion dynamic, possibly by relying on their general understanding. Nonetheless, they quickly gather necessary knowledge and finetune their person-specific predictions to become more accurate. To estimate the speed with which people acquire the information necessary to make accurate predictions at the level of a close friend, we conducted an exploratory extrapolation of this model. This analysis suggested that, under the assumption of linearity, participants need approximately 61 days to reach the accuracy level of close friends.

Group-level accuracy.—We next tested whether individuals could accurately predict the average group member's emotion transitions, using the same analyses as in Study 1. We first conducted a one sample *t* test on r-to-z transformed, per-subject correlations between group ratings and group-actual. The mean r-to-z transformed correlation was significantly above zero ($M = 0.94$, average $r = .68$, CI [0.87, 1.02], $d = 2.31$; Figure 3), indicating that participants have an accurate understanding of the aggregate patterns of emotion transitions in their new group. However, group-level accuracy from new college students is significantly lower than its counterpart obtained from the older college students in Study 1 ($F(1, 207) = 11.59$, $p < .001$)

We also examined the contribution of participants' group-level understanding to predicting the aggregate emotion transition patterns. In a linear mixed effects model, we used Group-Actual and Self ratings to predict Group ratings. Random intercepts were included for subjects nested in dyads, as well as for items (emotion pairs). A significant relationship between group-actual and group ratings in this model would indicate that group-level understanding independently contributes to accurate aggregate level predictions above and beyond participants' self-knowledge. Indeed, we found that group-ratings significantly predicted group ratings after controlling for self ratings ($b = 0.05$, $\beta = 0.05$, $t(8654) = 4.54$, $p < .001$).

These results indicate that participants can make accurate predictions about group-level transitions within only a few weeks of joining a new community. We next examined whether people accumulate this group-level knowledge over time. We tested the relationship between duration of group membership and group-level accuracy. How well participants can predict an average group member's emotion transitions was positively correlated with the number of days the student had been on campus (r(114) = 0.20, CI [0.03, 0.36]), suggesting that people can quickly learn group-level emotion dynamics, even over a short period of time.

To estimate participants' accuracy at zero acquaintance with the group, we conducted an exploratory linear model equivalent to this bivariate test, using number of days to predict group-level accuracy. The model had an estimated intercept of .75. That is, without having spent any time in the group, people can already somewhat accurately predict the group's emotion dynamics, possibly by relying on their general understanding. Nonetheless, they quickly finetune their group-level predictions to become more accurate. To estimate the speed with which people acquire the information necessary to achieve the level of accuracy of a longstanding community member, we conducted an exploratory extrapolation of this model. This analysis suggested that, under the assumption of linearity, participants need approximately 46 days to make accurate predictions at the level of longstanding community members.

Social success.—Using bivariate correlations, we first tested the relation between person-specific accuracy and measures of relationship success (see Table 3). Person-specific accuracy was not significantly correlated with the roommates' responses on the Respondent Affection scale (r(114) = 0.11, CI [−0.07, 0.28]), the Reis-Shaver Intimacy model (r(114) = 0.17, CI [−0.004, 0.34]), or perceived closeness (r(114) = 0.02, CI [−0.16, 0.21]). As expected, in the current sample of new college roommates, more accurate prediction of emotion transitions did not yet translate into or reflect the quality of roommate relationships. Nonetheless, these results are directionally consistent with results from Study 1, suggesting that the positive relation between person-specific accuracy and relationship success might develop over time.

We next assessed the relation between group-level accuracy and general social success in the current new college student sample. The more accurately a student predicted the group's emotion transitions, the larger their social network size (r(114) = 0.29, CI [0.14, 0.43]) and support network size (r(114) = 0.24, CI [0.07, 0.39]). Group-level accuracy was negatively associated with loneliness (r(114) = −0.13) as in Study 1, though not statistically significantly so (CI [−0.30, 0.04]). The relation between group-level accuracy and loneliness was stronger in Study 1 than in Study 2, which is consistent with the hypothesis that the relation between group-level accuracy and general social success develops over time. On the other hand, the relation between group-level accuracy and social network measures was nonsignificant in Study 1 but significant in Study 2. In all likelihood, measures of social and support network reflect relationships prior to entering college. As such, their relationship with group-level accuracy should be interpreted with this caveat in mind.

Finally, we tested the extent to which measures of person-specific and group-level accuracy converge with the RMET. We found that participants' score on the RMET was strongly correlated with both their person-specific (r(114) = 0.34, CI [0.11, 0.52]) and general (r(114) = 0.43, CI [0.22, 0.60]) accuracy. These findings deviated from the results of Study 1, where we found no relation between RMET scores and predictive accuracy. This result suggests that at an early stage of dyadic relationship, accurate prediction of one's partner's emotion transitions might partially depend on accurate perceptions of their emotional states. However, RMET did not translate into social success in this sample (see Table 3). RMET was not associated with any measures of relationship success between roommates; RMET was positively associated with social network size ($r(114) = 0.21$, $CI = [0.02, 0.39]$), but not support network size or loneliness.

Discussion

People's thoughts and feelings unfold over time. These emotion dynamics often follow predictable patterns — happiness is more likely to follow awe than anger; clarity is more likely to follow thinking than pride. However, emotion dynamics are also idiosyncratic. They can vary widely from person to person and from group to group. The current set of studies demonstrates that people can make accurate, fine-tuned predictions of emotion transitions for both individuals and groups. These findings thus highlight a novel set of social–cognitive skills, namely social predictions, as well as the implications of these skills for social success.

We found evidence that people can make accurate predictions of emotion transitions in two very different type of dyads: close friends and new roommates. Previous work has demonstrated that people can make accurate judgments about specific, well-known others in domains such as mental content (Stinson & Ickes, 1992) and behavior frequency (Vazire & Mehl, 2008). Our results extend these general findings about accurate social inferences into the domain of social prediction, namely the prediction of others' future states. Further, we provide evidence for how people accomplish this mind reading feat: people tailor their predictions about others by drawing on knowledge about their specific target. That is, people do not blindly apply their self-knowledge or their general understanding of emotion transitions to make person-specific predictions. While people understand that, in general, emotion dynamics follow predictable patterns, they also recognize the idiosyncrasies in their targets' dynamics. They fine-tune their predictions by taking these idiosyncrasies into account. The idea that people use person-specific knowledge to calibrate social predictions dovetails nicely with the previous finding that increased levels of empathic accuracy between male friends, as compared to between strangers, was accounted for by the detailed knowledge friends had about each other (Stinson & Ickes, 1992).

In addition, we found that it takes time for people to accumulate target-specific knowledge. This is evident on two different time-scales. First, we can look within the sample of new students. Students in this sample rapidly accrued the knowledge they needed in order to make accurate predictions about both their roommate and their community. Students who knew their roommate for only a few weeks were already much better at predicting their roommate than people who knew their roommate for only a few days. However, a few weeks is not nearly enough time to learn all one needs to know in order to make accurate predictions. We can see the effect of additional time by comparing our sample of new roommates to our sample of established friends. New dyads were significantly less accurate than dyads in longstanding relationships. We found similar effects when looking at changes in accuracy about the group as well. People in new communities can already make accurate predictions about an average group member, but they do better and better with more exposure to the group, and longstanding group members outperform newer ones.

People gradually acquire the knowledge that they need and become more accurate in their predictions over time. These findings highlight the importance of target-specific knowledge for fine-tuning social predictions.

We found evidence that people can accurately predict emotion transitions for their local community. We suggest that people solve this group prediction problem by accumulating information about their specific social group to gain a more accurate understanding of group-level emotion dynamics. Indeed, first-year students were less accurate than upperclassman students who had more time to accumulate group knowledge, and first-year students who participated shortly after arriving on campus were less accurate than students who had been on campus for longer. That said, we did not measure how accurate people were about any broader social group (e.g., Americans, people in general), so it is possible that people were able to be accurate about their local group by simply applying general knowledge in making group-level predictions. Future research should aim to provide direct evidence of group specificity by collecting predictions at both the community level and the broader group level.

Our results raise important questions about the process by which people learn to make person- and group-specific predictions. People may learn to make target-specific predictions in at least two ways. One possibility is that people learn incrementally through direct observations. People might observe and accumulate many individual instances of emotion transition over time and then construct their target-specific mental models of emotion dynamics by simple tallying. Alternatively, target-specific learning might be scaffolded by prior beliefs over how different emotion transitions tend to co-occur. Guided by such abstract knowledge, people could make inductive inferences about a specific target's unobserved emotion transitions after accumulating a small number of observations. The two hypothesized learning processes make different predictions about how long the learning process might take; the former requires a large amount of input that could only be acquired over a long period of time, whereas the latter requires only a few observations before generalization is possible, and would be much less time consuming. Here, we find that even within the very early stage of relationship formation, those who had interacted longer before completing the study tended to be more accurate. This finding favors the hypothesis that people rely on inductive inferences to quickly hone their target-specific mental models, rather than building these models from scratch. Future research should further investigate how abstract knowledge and inductive inferences facilitate learning about specific individual targets.

Accurate social predictions rely on target-specific knowledge. As a result, predictive accuracy should be partially dissociable from more traditional constructs of social cognition, such as social perception. We found that accurate person-specific predictions were highly correlated with the RMET in new dyads, whereas the same association was much weaker in established dyads. Local perceptual information, such as facial expressions and tones of voice, might serve as the most available and effective input about others' internal states at early stages of relationship formation. That is, the ability to infer mental experiences from the perceptible might be important for social predictions early on. As relationships develops, however, people need to go beyond the immediately observable in order to refine their understanding of a target's emotion dynamics. This further refinement might require the additional ability to learn and represent statistical contingencies over a longer timescale (Buchsbaum, Griffiths, Plunkett, Gopnik, & Baldwin, 2015) or the ability to make complex social and causal attributions (Alicke, Mandel, Hilton, Gerstenberg, & Lagnado, 2015). How well people fare in their social lives likely depends on how well they can not only reactively process indications about others' mental states that are already in place but also proactively form expectations about how others might think, feel, and act in the future. Future research should attempt to further investigate the extent to which social predictions might be a novel domain of social cognition using more comprehensive approaches.

Our findings offer preliminary evidence that social predictions bestow important social advantages. Long-term close friends that more accurately predict each other's emotion dynamics enjoy better relationship, and long-term community members that more accurately grasp their group's emotion dynamics enjoy better general social wellbeing. These findings converge with previous literature on how social–cognitive abilities positively relate to social well-being and social success (Banerjee et al., 2011; Bosacki & Wilde Astington, 1999; Gleason et al., 2009; Morelli, Ong, Makati, Jackson, & Zaki, 2017; Sened et al., 2017). However, this relation between accurate predictions and social success did not hold among social agents newly introduced to a relationship and a community. The relationship between accurate predictions and social success likely emerges over time. Interestingly, this emerging process seems to take place quickly in the early courses of relationship formation. Exploratory analyses suggest that the association between person-specific accuracy and relationship success was stronger among students who completed the study later on during recruitment (see online supplemental materials). This result provides evidence that the interplay between accuracy and social success might start occurring shortly after the social context forms, and the dividends of learning to make accurate predictions might accrue over time.

However, there are several caveats to note about this finding. First, the correlations between predictive accuracy and social success, while predicted a priori, have small effect sizes in Study 1. Second, while we hypothesized a priori that these relations should not exist in Study 2, it is also possible that we were simply unable to detect a relation between predictive accuracy and social success due to our sample size. Given the small effect size of in Study 1, we might not be well-powered enough to detect these relations in Study 2, especially if they were already attenuated. Third, the relation between accuracy and social success did not hold for all measures of social success. Fourth, the cross-sectional nature of our comparison also does not allow us to eliminate the influence of self-selection and thus limits the strength of our claim that the benefit of social predictions accrues over time. Thus, our results provide only preliminary evidence for a relation between predictive accuracy and social success. Future investigations should aim to replicate these results at a larger scale in order to achieve the statistical powers needed to establish both the positive and the null findings with higher confidence.

If it is the case that social prediction enables social success, then we can further ask two questions about the nature of this relationship. First, does social prediction contribute more to social success than other components of social cognition, such as social perception? In the current sample, predictive accuracy was associated with social success at least to the same extent as, if not better than, did the RMET. Social relationships are interpersonal in nature (Schilbach et al., 2013). Social accuracy in most situations can be difficult to objectively assess, and within-person, in-lab measures, such as emotion recognition, need not align with how well a perceiver predicts an actual target's emotions (Zaki & Ochsner, 2011). In contrast, predictions of emotion transitions can be measured against empirically obtained benchmarks (Thornton & Tamir, 2017). Social prediction, as operationalized in the current study, is similarly a purposeful measure of accuracy. It is thus a useful assay of real-world social ability precisely because it aims to map real-world experiences. It is worth noting that the current study measured accuracy against self-reported experiences, rather than experience-sampled ones. Nevertheless, this study found similar levels of accuracy ($\rho_{specific} = 0.56$, $\rho_{group} = 0.76$) as three studies with experience-sampled benchmarks (ρs = 0.77, 0.68, and 0.79; Thornton & Tamir, 2017). Nonetheless, future research should consider using empirical benchmarks to measure person-specific accuracy, to fully capture the relation between social prediction and social success. Future work should also try to further establish the convergent and discriminant validities of social prediction against more ecologically sound, open-ended measures of conventional social–cognitive ability (Betz, Hoemann, & Barrett, 2019; Cassels & Birch, 2014).

Second, to what extent does predictive accuracy actually cause social success? Our results are consistent with the hypothesis that accurate social prediction leads to social success. However, it is equally possible that people in better relationships are simply more motivated to be accurate in their predictions about their target, or that a third variable causes both. Similarly, while it is possible that higher group-level accuracy leads to higher general social success, it is also possible that frequent exposure to the social group underlies both accuracy and social success. The cross-sectional and correlational nature of the current study allows us to draw only non-directional conclusions about the relation between social predictions and social success. Future studies could resolve this issue by employing a longitudinal design and tracking how predictive accuracy and social success both develop over time. A longitudinal design would allow researchers to make stronger directional claims about the relation between predictive accuracy and social success. Furthermore, a longitudinal design would allow researchers to investigate how other variables known to impact relationship formation, such as perceived and objective similarity between the dyad members (Bahns et al., 2017), might impact and interact with predictive accuracy in a developing relationship.

Finally, it is important to note that interpersonal accuracy can be conceptualized and measured in various ways. Accuracy in the current work, in the domain of predicting emotions, has been indexed using correlational metrics between a person's prediction and either self-reported or experience-sampled ground truths. A similar correlational approach is also taken in the SAM (Biesanz, 2010). This approach conceptualizes accuracy as the relative correspondence between two measures across a wide range of items. However, accuracy can also be conceptualized as the absolute numerical agreement between measures. One prominent example of this approach can be found in the affective forecasting literature (Gilbert, Pinel, Wilson, Blumberg, & Wheatley, 1998; Wilson & Gilbert, 2003), which finds biases in people's predictions by looking at deviations in the magnitude of a predicted emotion on a smaller number of emotions. Future studies should combine more complex designs, such as those containing network structures, with varying analytical approaches like the SAM, in order to gain a more nuanced understanding of how people accurately predict others' emotions.

Navigating daily social life is one of human beings' crowning achievements. The social world demands that we constantly interact with a wide array of individuals, each with their own complex characteristics and each tied to us in different ways. Most people expertly handle these challenges. The present study highlights that people can make accurate predictions about others' future emotions at multiple levels of specificity, ranging from well-known friends to personally meaningful social groups. Our findings add a new layer to how powerfully and flexibly our cognitive system deals with demanding social tasks but also indicate that there is still much to explore.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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References

Alicke MD, Mandel DR, Hilton DJ, Gerstenberg T, & Lagnado DA (2015). Causal conceptions in social explanation and moral evaluation: A historical tour. Perspectives on Psychological Science, 10, 790–812. 10.1177/1745691615601888 [PubMed: 26581736]

Ambady N (2010). The perils of pondering: Intuition and thin slice judgments. Psychological Inquiry, 21, 271–278. 10.1080/1047840X.2010.524882

Ames DR (2004). Strategies for social inference: A similarity contingency model of projection and stereotyping in attribute prevalence estimates. Journal of Personality and Social Psychology, 87, 573–585. 10.1037/0022-3514.87.5.573 [PubMed: 15535772]

Bahns AJ, Crandall CS, Gillath O, & Preacher KJ (2017). Similarity in relationships as niche construction: Choice, stability, and influence within dyads in a free choice environment. Journal of Personality and Social Psychology, 112, 329–355. 10.1037/pspp0000088 [PubMed: 26828831]

Banerjee R, Watling D, & Caputi M (2011). Peer relations and the understanding of faux pas: Longitudinal evidence for bidirectional associations. Child Development, 82, 1887–1905. 10.1111/j.1467-8624.2011.01669.x [PubMed: 22023260]

Baron-Cohen S, Jolliffe T, Mortimore C, & Robertson M (1997). Another advanced test of theory of mind: Evidence from very high functioning adults with autism or Asperger syndrome. Journal of Child Psychology and Psychiatry, 38, 813–822. 10.1111/j.1469-7610.1997.tb01599.x [PubMed: 9363580]

Barrett LF (2017). The theory of constructed emotion: An active inference account of interoception and categorization. Social Cognitive and Affective Neuroscience, 12, 1833. 10.1093/scan/nsx060 [PubMed: 28472391]

Barrett LF, Mesquita B, & Gendron M (2011). Context in emotion perception. Current Directions in Psychological Science, 20, 286–290. 10.1177/0963721411422522

Betz N, Hoemann K, & Barrett LF (2019). Words are a context for mental inference. Emotion, 19, 1463–1477. 10.1037/emo0000510 [PubMed: 30628815]

Biesanz JC (2010). The social accuracy model of interpersonal perception: Assessing individual differences in perceptive and expressive accuracy. Multivariate Behavioral Research, 45, 853–885. 10.1080/00273171.2010.519262 [PubMed: 26795267]

Bosacki S, & Wilde Astington J (1999). Theory of mind in preadolescence: Relations between social understanding and social competence. Social Development, 8, 237–255. 10.1111/1467-9507.00093

Buchsbaum D, Griffiths TL, Plunkett D, Gopnik A, & Baldwin D (2015). Inferring action structure and causal relationships in continuous sequences of human action. Cognitive Psychology, 76, 30–77. 10.1016/j.cogpsych.2014.10.001 [PubMed: 25527974]

Buote VM, Pancer SM, Pratt MW, Adams G, Birnie-Lefcovitch S, Polivy J, & Wintre MG (2007). The importance of friends: Friendship and adjustment among 1st-year university students. Journal of Adolescent Research, 22, 665–689. 10.1177/0743558407306344

Campbell KE, Marsden PV, & Hurlbert JS (1986). Social resources and socioeconomic status. Social Networks, 8, 97–117. 10.1016/S0378-8733(86)80017-X

Cassels TG, & Birch SAJ (2014). Comparisons of an open-ended vs. forced-choice 'mind reading' task: Implications for measuring perspective-taking and emotion recognition. PLoS ONE, 9, e93653. 10.1371/journal.pone.0093653 [PubMed: 25474645]

Cunningham WA, Dunfield KA, & Stillman PE (2013). Emotional states from affective dynamics. Emotion Review, 5, 344–355. 10.1177/1754073913489749

Davidson RJ (2004). Well-being and affective style: Neural substrates and biobehavioural correlates. Philosophical Transactions of the Royal Society of London Series B, Biological Sciences, 359, 1395–1411. 10.1098/rstb.2004.1510 [PubMed: 15347531]

Decety J, & Jackson PL (2004). The functional architecture of human empathy. Behavioral and Cognitive Neuroscience Reviews, 3, 71–100. 10.1177/1534582304267187 [PubMed: 15537986]

Epley N (2004). A tale of tuned decks? Anchoring as accessibility and anchoring as adjustment. In Koehler DJ & Harvey N (Eds.), Blackwell handbook of judgment and decision making (pp. 240–257). Hoboken, NJ: Blackwell Publishing Ltd. 10.1002/9780470752937.ch12

Funder DC (1995). On the accuracy of personality judgment: A realistic approach. Psychological Review, 102, 652–670. 10.1037/0033-295X.102.4.652 [PubMed: 7480467]

Furr RM (2008). A framework for profile similarity: Integrating similarity, normativeness, and distinctiveness. Journal of Personality, 76, 1267–1316. Retrieved from https://onlinelibrary-wiley-com.ezproxy.princeton.edu/doi/full/10.1111/j.1467-6494.2008.00521.x [PubMed: 18705644]

Gendron M, Roberson D, van der Vyver JM, & Barrett LF (2014). Perceptions of emotion from facial expressions are not culturally universal: Evidence from a remote culture. Emotion, 14, 251–262. 10.1037/a0036052 [PubMed: 24708506]

Gershman SJ, Gerstenberg T, Baker CL, & Cushman FA (2016). Plans, habits, and theory of mind. PLoS ONE, 11, e0162246. 10.1371/journal.pone.0162246 [PubMed: 27584041]

Gilbert DT, Pinel EC, Wilson TD, Blumberg SJ, & Wheatley T (1998). Immune neglect: A source of durability bias in affective forecasting. Journal of Personality and Social Psychology, 75, 617–638. 10.1037/0022-3514.75.3.617 [PubMed: 9781405]

Gleason KA, Jensen-Campbell LA, & Ickes W (2009). The role of empathic accuracy in adolescents' peer relations and adjustment. Personality and Social Psychology Bulletin, 35, 997–1011. 10.1177/0146167209336605 [PubMed: 19498068]

Gopnik A, & Wellman HM (2012). Reconstructing constructivism: Causal models, Bayesian learning mechanisms, and the theory theory. Psychological Bulletin, 138, 1085–1108. 10.1037/a0028044 [PubMed: 22582739]

Gordon R (1986). Folk psychology as simulation. Mind & Language, 1, 158–171. 10.1111/j.1468-0017.1986.tb00324.x

Gow AJ, Pattie A, Whiteman MC, Whalley LJ, & Deary IJ (2007). Social support and successful aging. Journal of Individual Differences, 28, 103–115. 10.1027/1614-0001.28.3.103

Gross JJ (2002). Emotion regulation: Affective, cognitive, and social consequences. Psychophysiology, 39, 281–291. 10.1017/S0048577201393198 [PubMed: 12212647]

Heller AS, Fox AS, Wing EK, McQuisition KM, Vack NJ, & Davidson RJ (2015). The neurodynamics of affect in the laboratory predicts persistence of real-world emotional responses. The Journal of Neuroscience, 35, 10503–10509. 10.1523/JNEURO-SCI.0569-15.2015 [PubMed: 26203145]

Ickes W (1993). Empathic accuracy. Journal of Personality, 61, 587–610. 10.1111/j.1467-6494.1993.tb00783.x

Ickes W, Stinson L, Bissonnette V, & Garcia S (1990). Naturalistic social cognition: Empathic accuracy in mixed-sex dyads. Journal of Personality and Social Psychology, 59, 730–742. 10.1037/0022-3514.59.4.730

Jussim L, Crawford JT, & Rubinstein RS (2015). Stereotype (in)accuracy in perceptions of groups and individuals. Current Directions in Psychological Science, 24, 490–497. 10.1177/0963721415605257

Kolb KH (2014). Emotional subcultures. Sociology Compass, 8, 1229–1241. 10.1111/soc4.12207

Kuppens P, Oravecz Z, & Tuerlinckx F (2010). Feelings change: Accounting for individual differences in the temporal dynamics of affect. Journal of Personality and Social Psychology, 99, 1042–1060. 10.1037/a0020962 [PubMed: 20853980]

Martinez L, Falvello VB, Aviezer H, & Todorov A (2016). Contributions of facial expressions and body language to the rapid perception of dynamic emotions. Cognition and Emotion, 30, 939–952. 10.1080/02699931.2015.1035229 [PubMed: 25964985]

Mendelson MJ, & Aboud FE (1999). Measuring friendship quality in late adolescents and young adults: McGill Friendship Questionnaires. Canadian Journal of Behavioural Science/Revue Canadienne Des Sciences Du Comportement, 31, 130–132. 10.1037/h0087080

Mendelson MJ, & Kay AC (2003). Positive feelings in friendship: Does imbalance in the relationship matter? Journal of Social and Personal Relationships, 20, 101–116. 10.1177/02654075030201005

Mesquita B, Boiger M, & De Leersnyder J (2016). The cultural construction of emotions. Current Opinion in Psychology, 8, 31–36. 10.1016/j.copsyc.2015.09.015 [PubMed: 29506799]

Morelli SA, Ong DC, Makati R, Jackson MO, & Zaki J (2017). Empathy and well-being correlate with centrality in different social networks. Proceedings of the National Academy of Sciences of the United States of America, 114, 9843–9847. 10.1073/pnas.1702155114 [PubMed: 28851835]

Newport EL, & Aslin RN (2004). Learning at a distance I. Statistical learning of non-adjacent dependencies. Cognitive Psychology, 48, 127–162. 10.1016/S0010-0285(03)00128-2 [PubMed: 14732409]

R Core Team. (2018). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Reis HT, & Shaver P (1988). Intimacy as an interpersonal process. In Duck S, Hay DF, Hobfoll SE, Ickes W, & Montgomery BM (Eds.), Handbook of personal relationships: Theory, research and interventions (pp. 367–389). Hoboken, NJ: Wiley.

Rinck M, Glowalla U, & Schneider K (1992). Mood-congruent and mood-incongruent learning. Memory & Cognition, 20, 29–39. 10.3758/BF03208251 [PubMed: 1549063]

Russell DW (1996). UCLA loneliness scale (version 3): Reliability, validity, and factor structure. Journal of Personality Assessment, 66, 20–40. 10.1207/s15327752jpa6601_2 [PubMed: 8576833]

Schilbach L, Timmermans B, Reddy V, Costall A, Bente G, Schlicht T, & Vogeley K (2013). Toward a second-person neuroscience. Behavioral and Brain Sciences, 36, 393–414. 10.1017/S0140525X12000660 [PubMed: 23883742]

Sened H, Lavidor M, Lazarus G, Bar-Kalifa E, Rafaeli E, & Ickes W (2017). Empathic accuracy and relationship satisfaction: A meta-analytic review. Journal of Family Psychology, 31, 742–752. 10.1037/fam0000320 [PubMed: 28394141]

Skerry AE, & Saxe R (2015). Neural representations of emotion are organized around abstract event features. Current Biology, 25, 1945–1954. 10.1016/j.cub.2015.06.009 [PubMed: 26212878]

Stinson L, & Ickes W (1992). Empathic accuracy in the interactions of male friends versus male strangers. Journal of Personality and Social Psychology, 62, 787–797. 10.1037/0022-3514.62.5.787 [PubMed: 1593418]

Tamir DI, & Mitchell JP (2013). Anchoring and adjustment during social inferences. Journal of Experimental Psychology: General, 142, 151–162. 10.1037/a0028232 [PubMed: 22506753]

Tamir DI, & Thornton MA (2018). Modeling the predictive social mind. Trends in Cognitive Sciences, 22, 201–212. 10.1016/j.tics.2017.12.005 [PubMed: 29361382]

Thornton MA, & Tamir DI (2017). Mental models accurately predict emotion transitions. Proceedings of the National Academy of Sciences of the United States of America, 114, 5982–5987. 10.1073/pnas.1616056114 [PubMed: 28533373]

Tsai JL (2007). Ideal affect: Cultural causes and behavioral consequences. Perspectives on Psychological Science, 2, 242–259. 10.1111/j.1745-6916.2007.00043.x [PubMed: 26151968]

Vazire S, & Mehl MR (2008). Knowing me, knowing you: The accuracy and unique predictive validity of self-ratings and other-ratings of daily behavior. Journal of Personality and Social Psychology, 95, 1202–1216. 10.1037/a0013314 [PubMed: 18954202]

Waytz A, & Mitchell JP (2011). Two mechanisms for simulating other minds: Dissociations between mirroring and self-projection. Current Directions in Psychological Science, 20, 197–200. 10.1177/0963721411409007

Welborn BL, & Lieberman MD (2015). Person-specific theory of mind in medial pFC. Journal of Cognitive Neuroscience, 27, 1–12. 10.1162/jocn_a_00700 [PubMed: 25208740]

Willis J, & Todorov A (2006). First impressions: Making up your mind after a 100-ms exposure to a face. Psychological Science, 17, 592–598. 10.1111/j.1467-9280.2006.01750.x [PubMed: 16866745]

Wilson TD, & Gilbert DT (2003). Affective forecasting. In Zanna MP (Ed.), Advances in experimental social psychology (Vol. 35, pp. 345–411). Cambridge, MA: Elsevier Academic Press. 10.1016/S0065-2601(03)01006-2

Zaki J, & Ochsner K (2011). Reintegrating the study of accuracy into social cognition research. Psychological Inquiry, 22, 159–182. 10.1080/1047840X.2011.551743

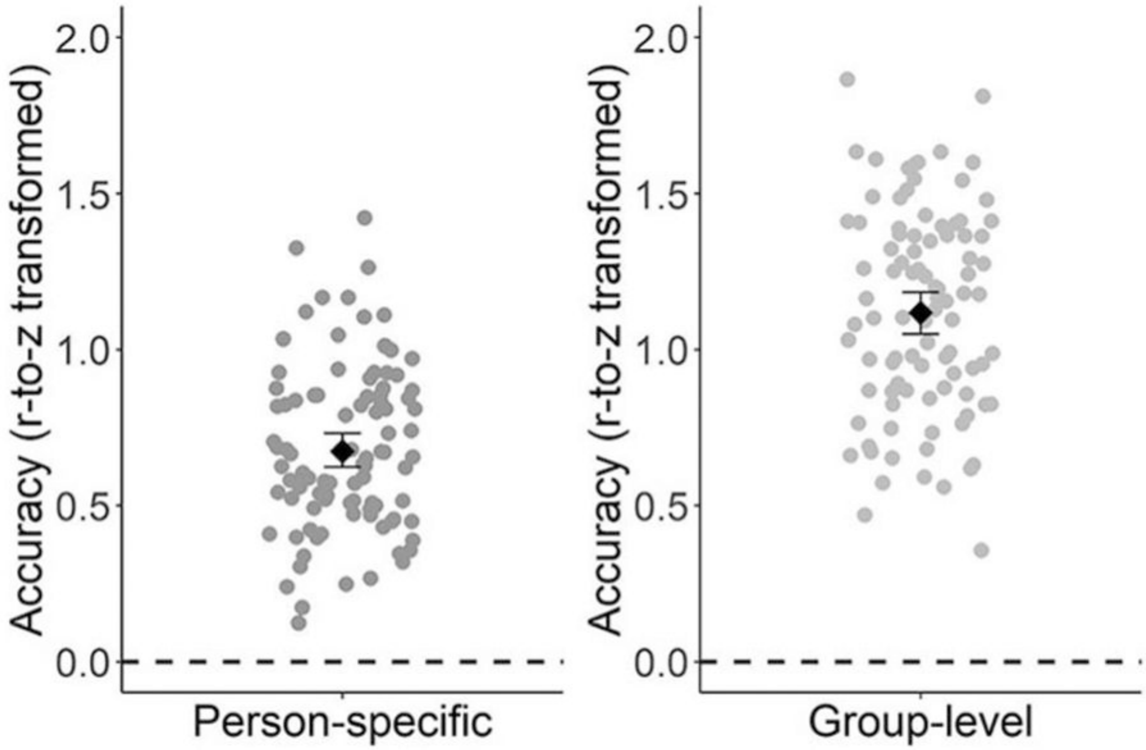

Figure 1.

Person-specific and group-level accuracies. People made highly accurate predictions of the emotion transitions for both their friends (left panel) and average-group member (right panel). Points indicate r-z transformed accuracy for each participant, diamonds indicate means, error bars represent bootstrap 95% confidence intervals, and dashed line represents chance accuracy.

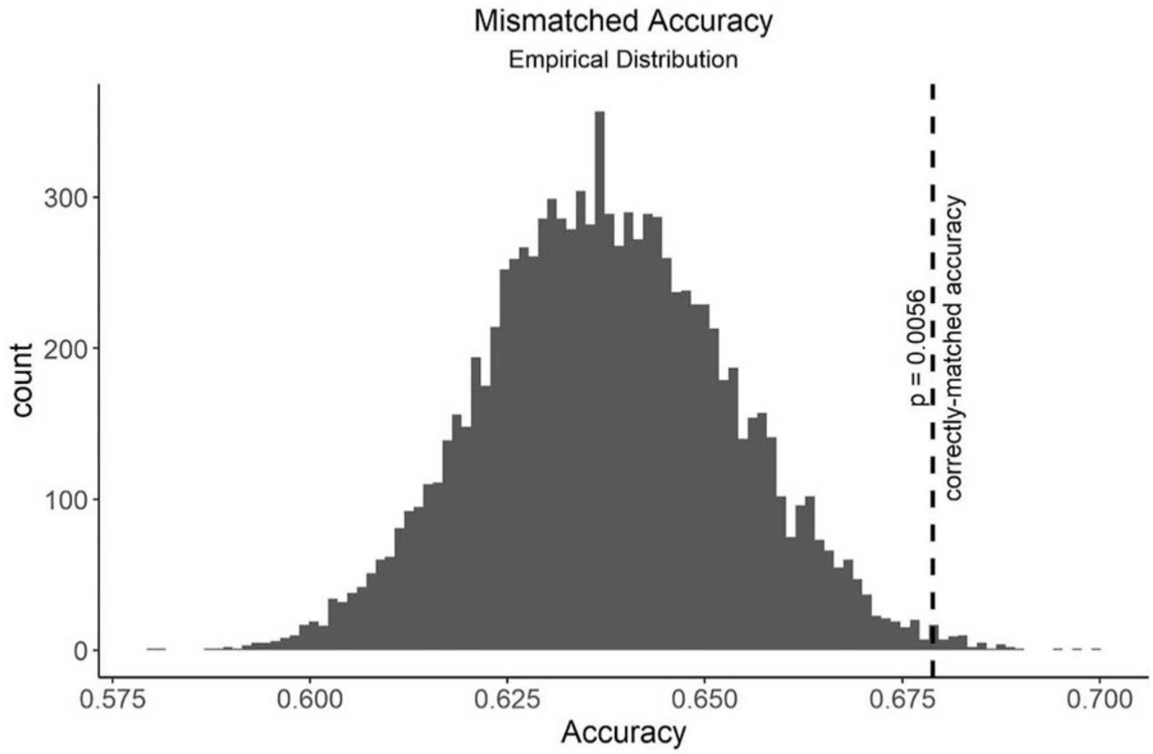

Figure 2.

Empirical distribution of mismatched accuracy. The distribution was obtained from 10,000 permutations. Dashed line represents the correctly matched person-specific accuracy.

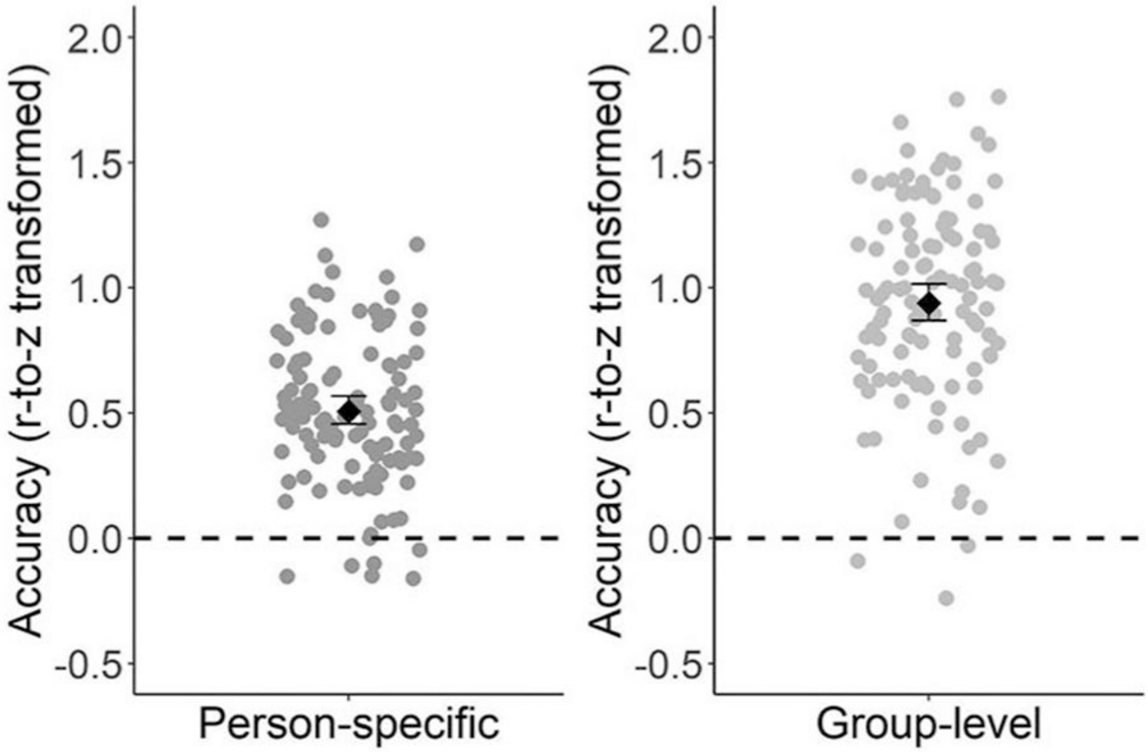

Figure 3.

Person-specific and group-level accuracies from Study 2. People made significantly accurate predictions of the emotion transitions of both their roommate (left panel) and average-group member (right panel). Points indicate r-z transformed accuracy for each participant, diamonds indicate means, error bars represent bootstrap 95% confidence intervals, and dashed line represents chance accuracy.

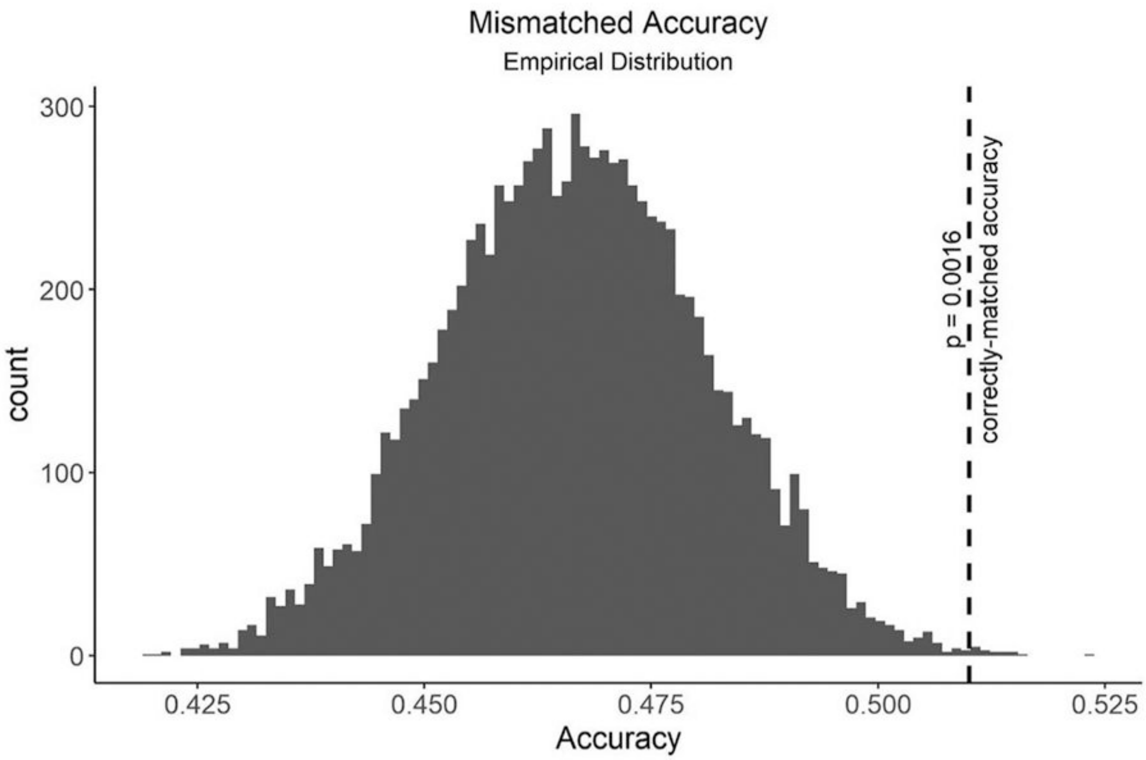

Figure 4.

Empirical distribution of mismatched accuracy. The distribution was obtained from 10,000 permutations. Dashed line represents the correctly matched person-specific accuracy.

Table 1

Emotion Words Included in the Emotion Transitions Task

Set 1	Set 2	Set 3
confident	nervous	satisfaction
grouchy	irritable	love
sad	lively	contempt
assertive	bold	disgust
unrestrained	talkative	embarrassment

Table 2

Correlations With Social Success Measures

Social success measures	Person-specific accuracy	Group-level accuracy	RMET
Relationship success			
Friend's respondent affection	0.15* [0.01, 0.30]		0.17 [−0.02, 0.33]
Friend's perceived closeness	0.12 [−0.04, 0.25]		0.21* [0.03, 0.38]
General social success			
Social network size		−0.15 [−0.35, 0.05]	0.13 [−0.08, 0.30]
Social support		0.05 [−0.15, 0.25]	0.05 [−0.15, 0.23]
Loneliness		−0.28* [−0.45,−0.10]	−0.08 [−0.29, 0.12]
Friendship duration	0.16* [0.003, 0.32]		0.07 [−0.16, 0.27]

Note. Pearson correlations between social success measures and Reading the Mind in the Eyes (RMET), person-specific accuracy, and group-level accuracy. Bootstrapped 95% confidence intervals are included in brackets. Significance is indicated by asterisks.

Table 3

Correlations With Social Success Measures From Study 2

Social success measures	Person-specific Accuracy	Group-level Accuracy	RMET
Relationship success			
Roommate's respondent affection	0.11 [−0.07, 0.28]		−0.07 [−0.27, 0.10]
Roommate's perceived closeness	0.02 [−0.16, 0.21]		−0.13 [−0.31, 0.05]
Roommate's Reis Shaver Intimacy	0.17 [−0.004, 0.34]		−0.03 [−0.22, 0.14]
General social success			
Social network size		0.29* [0.14, 0.43]	0.21* [0.02, 0.37]
Social support		0.24* [0.07, 0.39]	0.15 [−0.03, 0.30]
Loneliness		−0.13 [−0.30, 0.04]	−0.04 [−0.18, 0.12]
Relationship duration	0.23* [0.07, 0.37]		0.11 [−0.04, 0.25]
Days as group member		0.20* [0.03, 0.36]	0.04 [−0.13, 0.21]

Note. Pearson correlations between social success measures and Reading the Mind in the Eyes Test (RMET), the empathic concerns and the perspective taking subscales of the interpersonal reactivity index, person-specific accuracy, and group-level accuracy. Bootstrapped 95% confidence intervals are included in brackets. Significance is indicated by asterisks.