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Decoding the Dyad: Challenges in the Study of Individual Differences in Social Behavior

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Abstract

Social relationships are central to human life and are underpinned by the social interactions that constitute them. Both the behavioral sequences and the quality of these interactions vary significantly from individual to individual and conversation to conversation. This makes it difficult to understand the mechanisms that cause individual differences in social behavior and how such differences affect social outcomes. In order to gain insight into this problem, research must involve the study of real social interactions in parallel with experimental laboratory work. The aim of this review is to present three challenges in the study of face-to-face social behavior and to review results that have begun to address the question of how individual differences predict social behavior, which in turn determines social outcomes. Importantly, this review demonstrates that natural social behavior can be used as an outcome variable in experimental settings, making it possible to examine the mechanisms that drive social behavior and individual differences therein.

Keywords

social interaction, social skill, individual differences, research challenges

Human adults are extremely proficient social communicators. No two interactions are exactly alike, yet most people skillfully extemporize both verbal and nonverbal behaviors that fit the unique demands of their interpersonal encounters. Some of these behaviors will influence interaction quality, which evidence suggests predicts both immediate and more distal social outcomes such as liking, relationship development, well-being, and physical health (Holt-Lunstad & Clark, 2014; Umberson & Montez, 2010). It is therefore important to understand the mechanisms that drive social behavior, their interindividual differences, and how they relate to social outcomes.

What behaviors lead to successful social interactions? How can we predict their occurrence in individual interactions? At the moment, these questions remain unanswered. In part, this is because much research on social outcomes focuses on how differences in individual factors (e.g., social cognition—the ability to solve problems that involve information related to others' thoughts, feelings, intentions, behavior, etc.) correlate with social outcomes (e.g., social-support-network size; Kanai, Bahrami, Roylance, & Rees, 2012) without accounting for the actual face-to-face social behavior that drives these outcomes (Fig. 1a and 1c). Likewise, much theory on the factors that drive social behavior relies on findings that come from narrowly defined "pseudo-social" interactions (e.g., games in which participants complete simulated interactions with computerized partners; Kirk, Downar, & Montague, 2011; Mussel, Hewig, Allen, Coles, & Miltner, 2014) and from experiments in which the social stimuli resemble real-world stimuli only to a minimal extent (e.g., research examining how differences in neutral facial features predict trustworthiness judgments; Santos & Young, 2011; Stewart et al., 2012; van't Wout & Sanfey, 2008). How do these factors influence real face-to-face interactions?

It is logical that individual factors such as social-cognitive ability should underpin social ability. However, researchers have begun to note disconnections between social cognition and face-to-face social behavior. For example, many high-functioning individuals with autism

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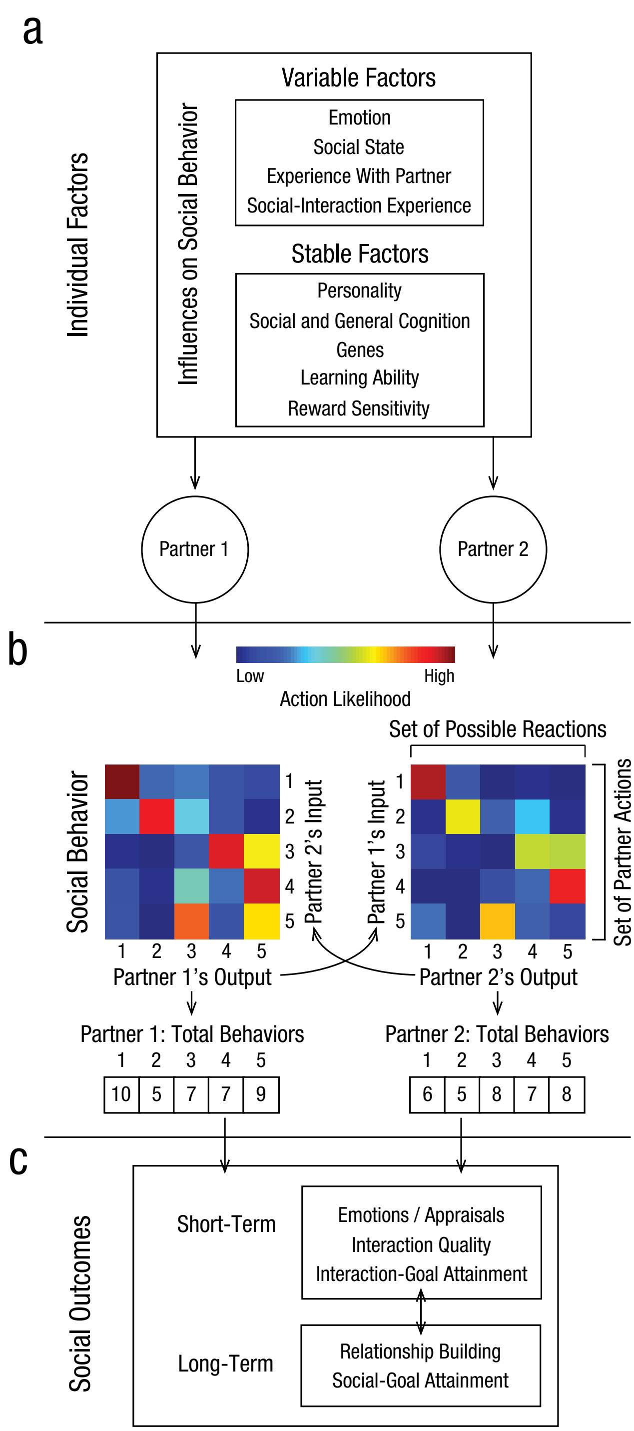

Fig. 1. Schematic linking individual differences with face-to-face social behavior and subsequent social outcomes. Stable and variable individual factors such as social-cognitive ability and emotional state serve as latent (indirectly observable) variables that underpin the social behaviors people produce (a). Social behavior tends to be studied in two ways. Most commonly, researchers produce frequency counts for behaviors of interest (b, bottom), which are then used to predict social outcomes. This method suffers from the disadvantage that simple frequency counts may mask important aspects of how participants react to partner input. To quantify this, one can calculate the conditional probabilities of each partner's behavior, dependent on the other partner's action. The "transition matrices" (b, top) depict the probability with which each person produces each of a set of possible responses to the partner (columns), depending on which of those behaviors the partner has just executed (rows). For example, the matrix on the right shows that when Partner 1 produces Action 1, Partner 2 has a high likelihood of responding with Action 1 and a low likelihood of responding with any other action. Because social interaction so strongly depends on another person's behavior, differences in the likelihood of these transitions may be better predictors of both immediate and longer-term social outcomes (c) than frequency counts of social behaviors.

possess adequate social-cognitive skills but remain awkward conversation partners (Stone & Gerrans, 2006). Brain injury can also impair social performance without impinging upon social cognition (Saver & Damasio, 1991), although the opposite may be true in schizophrenia, in which conserved interactions can occur in the context of significant social-cognitive deficits (McCabe, Leudar, & Antaki, 2004). Moreover, it is clear that individual differences in social ability exist among members of the general population (Skuse & Gallagher, 2011) despite their good performance on social-cognition measures. Thus, social-cognitive ability may not predict social behavior in a straightforward manner, likely because laboratory measures of social cognition differ too substantially from the requirements of face-to-face interaction. Self-report measures of social ability are equally problematic to interpret, as individuals' impressions of their social behavior may not be accurate (Heerey & Kring, 2007).

In addition to social cognition, factors including genes (Canli & Lesch, 2007), personality (Leary & Hoyle, 2009), emotion-regulation skill (Lopes, Salovey, Cote, & Beers, 2005), and sensitivity to reward (Pfeiffer et al., 2014) are candidate mechanisms that may determine the outcome of social interactions by shaping social behavior. However, in order to understand the processes by which social outcomes arise, it is necessary to study the intervening situation—namely, the behavior of two (or more) people interacting. Thus, researchers must begin to systematically examine behavior in face-to-face interactions, in parallel with traditional experimental work. Specifically, research in which natural interactions serve as a testbed for experimental findings and vice versa is necessary. This poses a series of significant challenges.

Challenge One: Quantifying Links Between Social Behavior and Outcomes

The first challenge is to identify which characteristics of individual social behavior determine the immediate outcomes of an interaction. Previous research has tended to take a targeted approach to this question by focusing on particular social skills. For example, evidence suggests that the frequency of certain behaviors, such as smiles or eye contact, predicts social outcomes (Fig. 1b, bottom; Hall, Coats, & LeBeau, 2005; Spezio, Huang, Castelli, & Adolphs, 2007). However, simple counts of behaviors neglect the complex interdependence between interaction partners. It is more likely that people's reactions to their conversation partners (e.g., reciprocating nonverbal cues, reacting to conversation topics, and regulating social outputs, given partner inputs) determine the outcome of an interaction (Heerey & Crossley, 2013; Hess & Bourgeois, 2010). The challenge for researchers, therefore, is to discover and map the links between social behavior and social outcomes, accounting for the interdependence in partners' behavior (Fig. 1b, top).

People's propensity to exchange genuine smiles during conversation illustrates this behavioral dependence. Research shows that in face-to-face interactions, participants match their partners' smile types, returning a partner's genuine smile with a genuine smile of their own, and doing likewise for polite smiles (Heerey & Crossley, 2013). However, it is not the frequency of genuine or polite smiles that determines how much a participant likes an interaction partner. Rather, it is the appropriateness of the returned smile. For example, individuals with social anxiety produce and return smiles at rates similar to those of non-anxious individuals (Alden & Taylor, 2004). However, we have shown that individuals with social anxiety often fail to match on smile type, returning a different smile than the one they received. Their inability to react appropriately to partner input led to reduced interaction quality ratings on behalf of their conversation partners (Heerey & Kring, 2007).

Importantly, if we had simply counted participants' genuine- and polite-smile frequency, we would have failed to find this significant predictor of social outcome. This example therefore highlights the importance of examining behaviors dependent on the actions of an interaction partner (e.g., a participant's likelihood of responding to a partner's genuine smile with a genuine smile) rather than simply measuring the frequency of specific behaviors in individuals. It is these "conditionally dependent" behavioral exchanges, of which smile reciprocity is one example, that are most likely to predict social outcomes. Other equally important examples of natural behavioral reciprocity that are capable of shaping interaction outcomes remain to be identified.

The "second-person" approach to the neuroscience of social behavior represents an important advance in this area (Schilbach et al., 2013). It advocates the use of dual-person experimental setups in which two real people interact, via avatars, in simple social interactions such as joint-attention paradigms. The use of individually controlled avatars provides a high degree of experimental control in ecologically valid interactions (Pfeiffer, Timmermans, Bente, Vogeley, & Schilbach, 2011). Thus, these simple experimental paradigms achieve the goal of allowing participants to engage directly in social interaction in an environment that allows precise measurement of social contingencies, as well as the neural correlates of those behaviors. This approach may be particularly important in elucidating behavioral deficits in psychiatric disorders (Timmermans & Schilbach, 2014). The use of virtual reality to examine interactions is an important approach that a number of laboratories are adopting (e.g., Iachini, Coello, Frassinetti, & Ruggiero, 2014; Riva et al., 2007). As information about specific behavioral exchanges, identified in unconstrained face-to-face

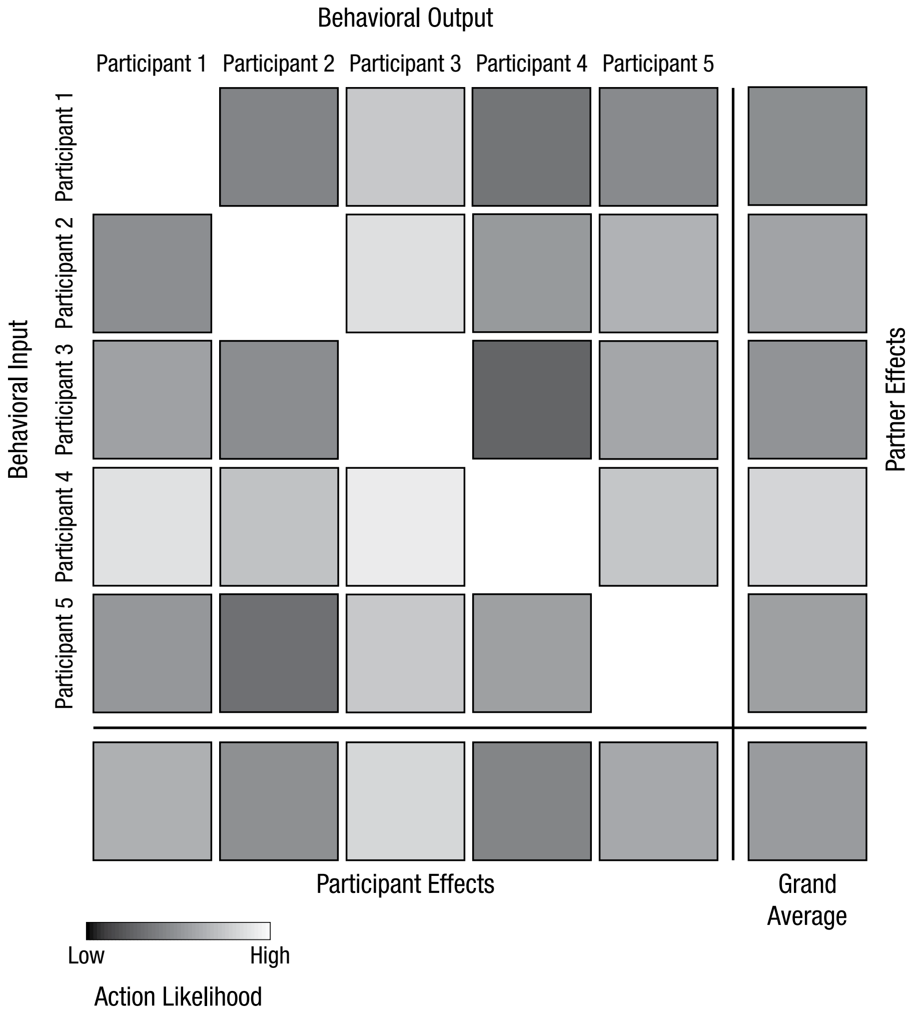

Fig. 2. Data from a hypothetical "speed-dating" style study in which each of five participants interacts with each other participant. Each square shows the likelihood with which each participant produces Behavior A (e.g., a genuine smile), dependent on receiving Behavior A from the social partner. For example, Participant 3 has an unusually high likelihood of returning genuine smiles (Column 3), and Participant 4 has an unusually high likelihood of seeing her smiles returned (Row 4; note that the diagonal is empty because participants cannot interact with themselves). The participant effects are the column averages, which show a participant's general action tendency across the set of partners. The partner effects are the row averages, which describe how participants' partners typically respond to them. People's deviations from the grand average of all participants' response probabilities across the set of interactions constitute stable individual differences in behavior. Using this logic, it is possible to compute similarity statistics on the transition matrices for single (as in the example) or multiple behaviors. The equations that govern the Social Relations Model (Kenny, Kashy, & Cook, 2006) can then be adapted to include these data.

interactions, begins to inform these methods, they will have a great deal of power to promote the experimental examination of contingent social behavior and its underpinning mechanisms.

Challenge Two: Identifying Stable Social Behaviors in Individuals

The second challenge for researchers who want to understand individual differences in social ability is to identify the unique contribution of each individual to his or her social interactions. This challenge stems from the problem that social-interaction data are not independent (Kenny, Kashy, & Cook, 2006). That is, individuals' social behavior depends strongly on that of their conversation partners. Because much work has focused on frequency counts rather than contingencies, few stable traits predicting social outcomes have been identified, despite a large literature on microprocesses in interaction (Back et al., 2011). Describing social behaviors as probabilities, conditioned on partner behavior as described in Figure 1, increases the likelihood of identifying stable traits. How often one smiles during an interaction will be strongly related to how often one's conversation partner smiles. However, the probability with which one returns a stranger's polite smile is much more likely to be a stable factor.

Nonetheless, the only way to examine the stability of individual differences in social behavior is to collect data from multiple interactions and code behavioral exchanges across partners in detail. One useful method of collecting such data is to ask participants to engage in a series of short interactions and code each participant's behavior throughout. "Speed dating" offers the perfect opportunity to meet this challenge, as each individual interacts with each other individual (Finkel & Eastwick, 2008). However, this approach generates huge volumes of video data, which require extensive decoding. Although the use of computer algorithms to code these data is improving (e.g., Zhang & Ji, 2005), truly naturalistic interactions, in which there are few constraints on participants' behavior, often require the use of trained human coders to identify behaviors and note their onset/offset times. Longer interactions and complicated coding schemes make this process challenging (Bakeman & Quera, 2011). Once the data are coded, researchers must then find analysis methods capable of dealing with the complexities of interaction data.

Kenny's Social Relations Model (SRM; Kenny et al., 2006) is the most prominent quantitative model for examining interdependent data. This model distinguishes the contributions of the "actor" from those of the "partner" and the specific pairing (the "relationship") to social variables. This is an elegant solution to the interdependence problem, as it allows researchers to quantify individual contributions within social pairings. However, the SRM and many models like it are designed for post-interaction ratings rather than face-to-face behavior (Kenny et al., 2006). To examine differences in the behavioral exchanges so important to interactions (i.e., how one partner reacts to the input of another), these models must be adapted to allow analysis of conditional probabilities for different actions (Fig. 2), given possible inputs (e.g., the likelihood of a participant's producing Behavior A, B, or C given that his or her social partner has produced Behavior A). Such reconceptualization of the SRM would allow the analysis of individual differences in the conditional probabilities of behavioral sequences, thereby extending research beyond simple microprocesses in social behavior to allow identification of stable social traits.

The ability to identify stable traits is advantageous because it provides specific research targets with clear links to social outcomes. Researchers can then design experiments targeting those traits for use in laboratory contexts or with neuroimaging methods, thereby enabling the identification of mechanisms that drive social behavior. It also has the potential to offer insight into typical social behavior and its development, as well as precise information about the breakdown of social interactions in disorders such as autism, schizophrenia, and depression. For example, irregularities in the exchange of eye-gaze behavior may lead to reductions in interaction quality for individuals with autism (Timmermans & Schilbach, 2014).

Challenge Three: Identifying the Mechanisms That Determine Social Behavior

A third challenge in the study of social ability lies in relating stable social behaviors to their underlying mechanisms. As an example, researchers in several fields of psychology have been using differences in people's associative learning ability (i.e., the ability to detect contingencies between events) to understand aspects of social behavior and cognition (Behrens, Hunt, & Rushworth, 2009; Behrens, Hunt, Woolrich, & Rushworth, 2008). This work has demonstrated that associative learning in 1-month-old infants predicts social cognition at 1 year (Reeb-Sutherland, Levitt, & Fox, 2012) and suggests that learning deficits may underpin the social deficits associated with autism (Solomon, Smith, Frank, Ly, & Carter, 2011). Indeed, associative learning ability may specifically underpin social and emotional development in childhood (Tarabulsy, Tessier, & Kappas, 1996), suggesting that individual differences in learning performance may be important drivers of people's social behavior, likely because at least some of the social behaviors people exchange serve as indicators of the contingencies active in a particular social environment (Heerey, 2014; Heerey & Velani, 2010).

Once basic relationships among individual factors, social behavior, and outcomes have been mapped, the final challenge is to experimentally test these links by manipulating either individual factors or social behavior and tracking the causal chain to observe changes in social behavior and/or social outcomes. For example, in one study, participants were asked to either mimic or not mimic a social partner's cues. In a conversation in which they listened to a partner's experiences, those under mimicry instructions experienced better social outcomes, including being better liked by their partners. The researchers therefore concluded that mimicry was the cause of the more positive social outcomes (Stel & Vonk, 2010).

Unfortunately, real social behavior is not always easy to manipulate. In the above example, participants received explicit instructions about how to behave.

Although successful in this study, constraining people's natural social behavior may artificially change the mappings between individual behavior and social outcomes. Ideally, therefore, researchers would influence the factors that drive social behavior in advance of interactions (e.g., by altering mood states) and observe subsequent changes in spontaneous social behavior and outcomes. This type of research design makes real social behavior the dependent variable in an experimental paradigm. Demonstrating that a specific social-behavior change is a consequence of a pre-interaction manipulation provides strong mechanistic evidence about the behavior in question.

For this approach to work, a tight integration of controlled laboratory tasks and observations of natural social behavior is essential. This will ensure that identified mechanisms underpin real-world functional behaviors rather than behaviors that are epiphenomena of the lab. Although it is not always easy to run parallel studies in both environments, efforts to do so can be highly beneficial because this convergence of methods makes it possible to generate strong mechanistic conclusions that apply to real social data (Heerey & Crossley, 2013). Ultimately, it should become possible to predict face-to-face social behavior based on performance differences in laboratory tasks.

Conclusions

Although the challenges of understanding individual differences in social behavior are significant, they are worth addressing. Evidence shows that social relationships are critical for physical and social well-being (Holt-Lunstad & Clark, 2014), meaning that enabling people to improve social outcomes will confer significant benefits in a variety of domains. In particular, this work will provide a foundation for mapping the complicated terrain of natural social behavior, thereby enabling researchers to explore why differences in social performance arise and how these differences relate to social outcomes, and to begin to understand the evolution of social behavior in the digital world.

Recommended Reading

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Kelley, H. H., & Thibaut, J. W. (1978). *Interpersonal relations: A theory of interdependence*. New York, NY: Wiley-Interscience. Provides information on social-interdependence theory.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). (See References). Provides an explanation and "operations manual" for the Social Relations Model.

Leary, M. R., & Hoyle, R. H. (Eds.). (2009). (See References). An excellent review of how individual factors—for example, differences in personality (e.g., extraversion, neuroticism) or cognitive style (e.g., optimism)—contribute to social behavior.

Schilbach, L., Timmermans, B., Reddy, V., Costall, V., Bente, G., Schlicht, T., & Vogeley, K. (2013). (See References). An excellent exposition of the second-person perspective, with insightful commentary.

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Declaration of Conflicting Interests

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