ARTICLE IN PRESS

Organizational Behavior and Human Decision Processes xxx (xxxx) xxx

Contents lists available at ScienceDirect

Organizational Behavior and Human Decision Processes

journal homepage: www.elsevier.com/locate/obhdp

The accurate judgment of social network characteristics in the lab and field using thin slices of the behavioral stream

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ARTICLE INFO

Keywords:
Accuracy
Social behavior
Person perception
Social judgment
Social networks
Thin slices
Personality
Social perception

ABSTRACT

When deciding whom to ally with or avoid, people benefit from assessing the quantity and quality of strangers' relationships with others. How accurately do people make such social network assessments? Across three lab studies and one preregistered field study, we tested whether people (total $N = 1545$) could make accurate judgments about a stranger's (total $N = 709$) social network characteristics after watching brief thin slice videos of the stranger or negotiating with them. The findings consistently demonstrated that perceivers accurately detected the size of a stranger's social networks and their gender and family composition, based on theoretically relevant social-behavioral tendencies and traits (e.g., extraversion, gender), but not how interconnected these social networks were. Perceivers also missed cues that could have facilitated greater accuracy. These data advance theory about adaptive social decision making in psychology, network science, sociology, and organizational behavior. We also provide the freely available Social Network Accuracy Test (SNAT) for future research: (https://osf.io/zgbse).

1. Introduction

Humans demonstrate a remarkable, perhaps biological, readiness to form and maintain memberships in groups and construct social networks (Baumeister & Leary, 1995; Durkheim, 1995). In fact, our long-term survival necessitates the successful formation and maintenance of group membership and social networks (Dunbar, 2008). Specifically, membership in social groups and networks allows us to rely on others for information, protection, aid, and resources, which maximizes our likelihood of survival (Brewer, 1997; Caporael, 1997; Ibarra et al, 2005; Lin, 2001). At the same time, affiliating with a stranger brings potential risk to the self and one's network. Therefore, when we first encounter a stranger, we must decide whether or not to affiliate with them and, if so, to what degree. Thus, one may be afforded advantage from making accurate inferences about others' states of mind, intentions, personality, and the company they keep—the latter of which science knows very little about: thus, the focus of the current research.

Have humans evolved to be able to accurately assess the quantity and quality of a stranger's relationships with others? The current research aims to determine whether, based on minimal social information, people can accurately infer the size, composition, and interconnectedness of strangers' social networks. Because this research is at the nexus of two fields, psychology and sociology, we ground the degree of uniqueness and potential value of the research question by contextualizing it within each discipline.

1.1. The sociological and network perspective on social network accuracy

Constructing and maintaining social networks has powerful benefits (Burt, 1992, 2004; Coleman, 1990; Lin, 2001; Portes, 1998). Specifically, and consistent with empirical psychology, people may reap social, strategic, emotional, physical, and economic advantages if they make good decisions about whom to affiliate with and whom to exclude from their social network (Bearman & Moody, 2004; Ibarra et al., 2005; Smith & Christakis, 2008). "Networks can facilitate or inhibit action, but *people* are the source of action," Burt et al. (2013, p. 536, emphasis added) reminds us. A critical unanswered question about agency in social network research is whether people vary in the accuracy of their judgments about the strangers they encounter when deciding whether to affiliate or avoid (Emirbayer & Goodwin, 1994; Kilduff & Brass, 2010; Kilduff & Krackhardt, 1994; Small, 2009). For example, if one's goal is to make friends who will be trustworthy and provide social support, one

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https://doi.org/10.1016/j.obhdp.2021.09.002

may want to select those with a dense social network in which everyone knows everyone else; dense networks are associated with higher trust, less deception, and more social support (Burt, 1986; Fischer, 1982; Kadushin, 1983; Marsden, 1987). By contrast, if being strategic regarding one's career is the goal, one may wish to forge a relationship with someone who can offer valuable career advice; this may lead one to pursue others with large, diverse, or disconnected social networks. Thus, being able to accurately detect another person's social network size and composition may hold strategic value (Burt, 2004, 2007; Burt & Ronchi, 2007; Mehra et al., 2006).

Prior work examining network cognition has found that they can encode, recall, and accurately judge novel social networks based on hypothetical descriptions of network relationships (Brashears, 2013; Brashears & Quintane, 2015; De Soto, 1960; Smith et al., 2020). Social network judgment accuracy, broadly defined, is the "degree of similarity between an individual's perception of the structure of informal relationships in a given social context and the actual structure of those relationships'' (Casciaro et al., 1999, p. 286). Foundational research on organizational networks showed early evidence that employees have an accurate sense of their co-workers' networks within their organization (Casciaro, 1998; Krackhardt, 1990; Krackhardt & Kilduff, 1990; for a review, see: Brands, 2013). Additional seminal work has shown that working full-time, being considered a friend by many others, positive affect, higher positional power, and greater achievement orientation facilitate accurate social network judgments by providing more opportunities and motivations to learn social network characteristics (Casciaro, 1998; Casciaro et al., 1999; Krackhardt, 1990).

Based on research in psychology, reviewed next, we hypothesize that the overall effect of social network judgment accuracy will generalize *beyond known others to strangers*. Can people accurately judge the network of a stranger—someone who does not belong to the same organization—based on minimal social information (e.g., a ~ 100-second video clip or brief social interaction over teleconference). While strangers lack information about each other, a good deal of evidence in the psychological literature suggests there are many reasons why people may be able to accurately judge at least some social network characteristics of strangers.

1.2. The psychological perspective on social network accuracy

There is a long history in clinical, forensic, industrial-organizational, personality, and social psychology testing whether people can make accurate judgments of a wide range of others' (strangers, acquaintances, friends, significant others, colleagues, etc.) personal attributes. Typically, perceivers in these studies observe a brief excerpt (i.e., "thin slice") of the behavioral stream, such as a photograph, an audio or video clip from the lab or field, or a short social interaction with another person or group (e.g., Ambady & Rosenthal, 1992; Carney et al., 2007; Carney & Harrigan, 2003; DePaulo, 1992; Ickes, 1993; Rogers et al., 2016). After the brief exposure, perceivers then make a judgment (or set of judgments) about the target individual(s). Hundreds of empirical studies demonstrate that humans do, indeed, make accurate judgments of many different characteristics, including emotional states (e.g., Ekman, 2003; Ekman et al., 1987; Ickes, 1993), personality traits (e.g., Borkenau & Liebler, 1993; Carney et al., 2007; Frank et al., 1993; Gifford, 1991), hierarchical rank (e.g., Schmid Mast & Hall, 2003, 2004), preferences (e.g., Stillman et al., 2010), biological predispositions (e.g., Rule et al., 2008; Rule et al., 2009), and other talents, intentions, and attributes (e.g., Carney & Harrigan, 2003; Murphy et al., 2003; Rogers, et al., 2016; Roney et al., 2006; Satterstrom et al., 2019; Stillman et al., 2014; ten Brinke et al., 2019). However, research on judgmental accuracy in the psychological sciences has not yet deeply investigated whether perceivers can make accurate assessments of a *stranger's social network characteristics*; thus, the focus of the current research (for a recent exception, see Alt et al., 2021).

How do people make accurate judgments about others based on such limited information? The dominant theory in the accuracy literature suggests a four-step process involving both the perceivers making the judgments and the targets who are being judged. First, targets must emit cues (verbal, nonverbal, paralinguistic, social behavioral, etc.) that are: (1) *relevant* to the characteristic being judged and (2) *available* to be observed to the perceiver. The perceiver must then (3) *observe* and detect/identify these cues and (4) correctly *utilize* relevant cues to form an accurate judgment (i.e., the Realistic Accuracy Model; RAM; Funder, 1995; 1999). In the current research, the characteristics being judged were social network characteristics with empirical relations (or a lack thereof) to observable behavior (Table 1). We predicted that, even in a zero-acquaintance context (i.e., one in which strangers are being judged), there are theoretical reasons to expect that people will make accurate judgments of at least some social network characteristics, especially when characteristics are particularly tied to observable social behaviors—such as another person's network size (see Table 1).

2. The current research

In four studies, we tested whether perceivers could accurately judge the social network characteristics of targets (Bernard et al., 1984; Moreno, 1934; Perry et al., 2018; Rossi, 1966; Wellman, 1993). Specifically, we tested whether perceivers could accurately detect four egocentric[1] network characteristics of strangers: size of the target's social network, composition (share of males vs. females and share of family vs. non-family in the target's network), and interconnectedness (how many of the target's social ties know one another).

Drawing on a long tradition in social network research, we focus on the interpersonal environments in which people live by examining egocentric networks, where a person is at the center (e.g., ego) and is surrounded by a network of their contacts. This allows us to study people across settings (Bernard et al., 1984; Moreno, 1934; Perry et al., 2018; Rossi, 1966; Wellman, 1993). Of course, one could study a universe of network characteristics; we selected the four target network characteristics (size, family composition, gender composition, and interconnectedness) because egocentric network research has focused a great deal of attention on each of them (Burt, 1984; Fischer, 1982; Marsden, 1987; McPherson et al., 2006; Wasserman & Faust, 1994) and they are linked to observable social behaviors (Table 1). Additionally, each has been shown to predict outcomes as varied as the availability of social support (Berkman & Glass, 2000; Fischer, 1982; Wellman & Wortley, 1990) to health and well-being (Berkman et al., 2000; Kadushin, 1983) to innovation and career attainment (Burt, 2004; Ibarra, 1992).[2] We followed past research in eliciting moderately strong social network ties with whom people discussed important matters, as these are the relationships

[1] An alternative approach is sociocentric, which requires gathering all network ties between pairs of people in a discrete universe, such as an organization. Sociocentric network analysis can use behavioral network data—for example, from behavioral communication records, or the roster method, in which participants are presented with a list of all people in a bounded network to identify social network relationships. We chose to study egocentric networks instead because they impose less of a cognitive burden on participants during data collection and are more likely to be linked to one's self-presentation and social behaviors in routine social interactions (Wasserman & Faust, 1994).

[2] Despite the importance of and past research on the racial composition of targets' networks (Flynn et al., 2010), we excluded this from our study for two reasons. First, when participants believe that a study is about race, it can lead them to respond differently than they otherwise would (e.g., Green et al., 2007). Second, we sampled our targets from a large West Coast university that was not racially diverse, thus compromising the distribution of targets' network racial composition. That said, we think understanding whether perceivers can detect a target's racial composition is a critical avenue for future research. To facilitate future research, we did collect data on our targets' racial composition and have made the videotape stimuli and network data freely available to researchers (more on this in Study 2a; https://osf.io/zgbse).

Table 1

Network Characteristics, Conceptual and Operational Definitions, and Likely Social-Behavioral Correlates.

Definitions and Operationalization	Possible Motivations for Network Judgment	Evidence of Underlying Network Cognition	Likely Social-Behavioral Correlates
Network Size: The number of other people in a person's network ("alters"). We measured network size with a standard important matters name-generator question (i.e., a question that generates names of one's network contacts; Burt, 1984; Fischer, 1982; Marsden, 1987, 1988; McPherson et al., 2006): "From time to time, most people discuss important matters with other people. Looking back over the last six months, who are the people with whom you discussed matters important to you?"	- Typically, the more network connections a person has, the more likely they are to be a conduit to a greater amount and variety of social resources; in brief, this reflects the degree of relational activity around a person (Marsden, 1987, 2002; Wellman & Wortley, 1990). For example, people with larger core discussion networks have greater access to major help in a crisis (Hurlbert et al., 2000).	- Perceivers can accurately recall alters in hypothetical networks (Brashears et al, 2016; Simpson & Borch, 2005; Simpson et al., 2011).	- People who tend to have larger social networks tend to be more extraverted (Feiler & Kleinbaum, 2015; Forret & Dougherty, 2001; Jensen-Campbell et al., 2002; Lee & Tsang, 2001; Ong et al., 2011; Wanberg & Kammeyer-Mueller, 2000). Those who are more extraverted tend to be more sociable and outgoing, and spend more time initiating interactions, talking, and interacting with others (John & Srivastava, 1999; Paunonen & Ashton 2001; Shipilov et al., 2014). People with larger networks are associated with emotional intelligence and the ability to resolve conflict through compromise, and have stronger implicit associations of the self with collaborative, rather than independent, attributes (Austin et al., 2005; Srivastava & Banaji, 2011; Zaccaro et al., 1991).
Family Composition: "Proportion family" is a measure of the kinship composition of a person's network. Proportion of family ties was measured as the number of family contacts (includes significant other and other family members) divided by the number of total contacts reported (Fischer, 1982; Marsden, 1987).	- Assessing the extent to which a target's social network is connected to their family members can send signals about their access to social and emotional support, financial aid, and their health and cultural capital (Bourdieu, 1984; Wellman & Wortley, 1990).	- Perceivers are better able to detect social network information that is linked to family because it is a familiar cultural schema (Brashears, 2013). Perceivers expect that people's social networks are composed of relationships with family members and, despite cultural variation in kinship systems, the existence of family schemata is universal. Relative to other types of recreational groups, such as club members, family is a stronger schema.	- Another characteristic of people whose networks consist of a greater proportion of kinship ties is conscientiousness, the Big Five personality trait (Asendorpf & Wilpers, 1998). This association may occur because more conscientious people feel obliged to maintain ties with family (rather than new relationships with non-kin), or close families may foster conscientiousness. People with networks characterized by greater contact and connection to family members tend to be women (Fischer & Oliker, 1983; Marsden, 1987; Moore, 1990). This has been attributed to dispositional and structural differences associated with gender; women may be more disposed to maintaining more family ties and fewer ties outside the family, and structural constraints associated with marriage, children, and employment shape the proportion of family in one's network (Chodorow, 1978; Fischer & Oliker, 1983; Gilligan, 1982; Wellman, 1984).
Gender Composition: "Proportion male" is a measure of the gender composition of a person's network. We measured the proportion of male ties by dividing the number of male contacts from the number of total contacts reported (Marsden, 1987).	- Because gender is a status characteristic, perceivers can be motivated to evaluate the extent to which people affiliate with the higher-status gender category, the proportion of male contacts in their social network. Given that men are often perceived to be associated with more power and resources, the proportion of one's network that is composed of male contacts may signal access to valuable resources and information.	- Perceivers expect that groups are composed of similar people; in other words, people expect homophily—in terms of formal, informal, and ascribed status as well as values, attitudes, and beliefs—in social networks (Lazarsfeld & Merton, 1954; McPherson et al., 2001). Gender is a universal primary social identity and status characteristic that perceivers use to confer group membership (Ridgeway, 1997, 2011).	- Men tend to have networks composed of a greater proportion of other men rather than women, excluding family members (Marsden, 1987; McPherson et al., 2001). Such gender homophily in networks is primarily driven by gender segregation in the set of potential contacts shaped by organizations, such as workplaces or voluntary associations. To the extent that a person's network is centered on content that is segregated by gender (e.g., work, politics, sports), the tendency for men to have a greater proportion of other men in their networks is larger (Bielby & Baron, 1986; Ibarra, 1992, 1997; Kalleberg et al., 1996; McPherson & Smith-Lovin 1982, 1986, 1987).
Interconnectedness: the relationship between one's network alters. More interconnected networks characterize dense interpersonal environments that typically contain less diverse alters. How interconnected one's social network is can provide clues about the extent to which a target is normatively embedded in a dense group.	- Greater interconnectedness can signal that a target has extensive social support available, which is associated with well-being and success (Burt, 1986; Fischer, 1982; Kadushin, 1983). It can also indicate that there are normative pressures towards conformity that could constrain a target (Marsden, 1987). On the other hand, people who have less dense networks that provide more opportunities for brokerage (a special case of low interconnectedness) may signal access to novel, unique, innovative, and creative information and resources (Burt, 1992).	- Perceivers pay more attention to groups in social structure, so much so that they perceive exaggerated boundaries between groups and more interactions within groups than actually take place (Cairns et al., 1985; De Soto, 1960; Freeman, 1992; Freeman & Webster, 1994; Kumbasar et al., 1994). Perceivers rely on small microstructures to make judgments about network interconnectedness. In other words, perceivers have strong social network schemas for interconnected networks: (1) triads, or three interconnected people, and (2) small worlds, or segregated and densely connected clusters of people bridged by popular brokers (Brashears & Quintane, 2015; Kilduff & Krackhardt, 2008).	- Greater interconnectedness is associated with being a woman, a higher need to belong, and being helpful or supportive (Brands & Kilduff, 2014). People with highly interconnected networks tend to possess more psychological health and less psychopathology, leading to less deception (Berkman & Glass, 2000; Litwin, 2003; Litwin & Shiovitz-Ezra, 2006). Conversely, less dense networks that allow for brokerage positions tend to be associated with being a man, agency, a desire for status, and competence (Alt et al., 2021; Brands & Kilduff, 2014).

Note: The exact nature of social network dynamics depends on the social context.

that shape one's self-presentation and through which key network processes, such as influence and socialization, occur (Burt, 1984: 317).[3] The second column of Table 1 lists potential social resources and types of social capital associated with each network characteristic that could motivate accurate judgments of those network characteristics by perceivers. The third column of Table 1 summarizes evidence of the associated network cognition from studies of memory and hypothetical networks.

Next, to develop our theoretical predictions about which social network characteristics are likely to be accurately judged, we drew upon on theory and empirical findings from both psychology and social network research. The fourth column in Table 1 lists the likely behavioral correlates of the four social network characteristics. For instance, people with larger networks tend to be more extraverted, and extraversion is linked to a host of observable behaviors (e.g., the expression of positive emotion, more speaking time, ease of public speaking). Therefore, to the extent perceivers can detect cues related to extraversion and use these cues when making judgments about network size, perceivers should be able to form accurate judgments of network size by using extraversion cues. Moreover, white American women (vs. men) tend to have a greater proportion of family members in their networks and more women (vs. men) in their networks; this depends on cultural values and the extent to which they are moderated by gender, race, ethnicity, and class, to name a few (Gaines et al., 1997; Marsden, 1987). Thus, to the extent that perceivers use gender as a cue, perceivers should be able to make accurate judgments about network family and gender composition. Likewise, network interconnectedness is associated with greater psychological health, less psychopathology, a need to belong, and less deception (Berkman & Glass, 2000; Litwin, 2003; Litwin & Shiovitz-Ezra, 2006); if perceivers detect a target's level of need to belong and use it to make accurate judgments of interconnectedness, perceivers should be likewise accurate at judging network interconnectedness. However, interconnectedness is highly related to trust, and deception is, on balance, accurately judged at approximately chance levels, suggesting that it may be particularly challenging to form accurate judgments of network interconnectedness (Bond & DePaulo, 2006; Levine, 2014; Levine et al., 1999).

Altogether, because network size, gender and family composition, and interconnectedness have social-behavioral correlates, we hypothesize that perceivers will be able to form accurate judgments about these four characteristics, with the least confidence in interconnectedness. However, our argument is conditional on perceivers observing these cues and using them when making judgments about a target's social network characteristics.

2.1. Overview of the four studies

In four studies, we tested whether perceivers could accurately judge four different social network characteristics (network size, gender composition, family composition, and interconnectedness). Study 1 contained two phases: in Phase 1, we constructed videotaped stimuli with rich criterion data on target participants' social networks ($n = 23$). In Phase 2, participant perceivers ($n = 375$) watched short, standardized videos (i.e., thin slices) of these targets and made judgments about their network characteristics. This design allowed us to compute accuracy coefficients separately for each of the four network characteristics. Studies 2a and 2b replicated the results from Study 1 with two new samples of perceivers ($n = 212$, and $n = 272$). A secondary goal of Studies 2a and 2b was to construct and provide preliminary validation data for an individual difference measure that assesses the degree to which an individual can accurately judge social network characteristics, called the Social Network Accuracy Test (SNAT). The SNAT, a 10-item video test, was made freely available to the research community to test additional questions not asked in the current research. All target videos and data, as well as raw data for additional network characteristics not tested in the current research, can be found here: https://osf.io/zgbse.

Study 3 extended this work by conceptually replicating our effects using an actual live dyadic negotiation task rather than pre-recorded videos. Study 3 increased the ecological validity of the research and greatly expanded and diversified our sample of perceived targets. Thus, with a larger target sample size (twenty-fold larger, $n = 686$), Study 3 was also able to investigate, with sufficient statistical power, which social behaviors perceivers used correctly to make accurate judgments about social network characteristics.

Across all of four studies, we reported how we determined sample sizes, and when and why data were excluded; data were not analyzed until collection was complete (Simmons et al., 2012). Our data, code, and survey materials are available in the Open Science Framework repository for this project (https://osf.io/zgbse). Additional analyses are also conducted throughout the manuscript and summarized in the Supplemental Materials. Finally, Study 3 was preregistered.

3. Study 1

Study 1, as is typical in accuracy research (e.g., Ambady & Rosenthal, 1992; Carney et al., 2007), was conducted in two phases. In Phase 1 (target stimulus collection), target video recordings and social network characteristic criterion data were collected for use in Phase 2. Phase 2 (perceiver judgments) was an accuracy study correlating perceivers' judgments of targets with targets' actual social network characteristics collected in Phase 1. Based on the evidence in Table 1, we predicted that accuracy about network size, family and gender composition, and interconnectedness is possible, so we tested all four characteristics.

3.1. Phase 1 method (constructing stimulus materials used in Phase 2)

Participants ("targets," going forward). Twenty-three self-identified white/European Americans completed all measures in an experimental laboratory at a West Coast university (39.1% male, 60.1% female; $Med_{age} = 21$, $SD = 6.2$).[4] Following standards employed in over 60 years of previous accuracy research, we aimed to collect 25 to 30 targets (e.g., 24 targets in the most ubiquitously used test of accuracy of facial expression, the Diagnostic Analysis of Nonverbal Accuracy; DANVA; Nowicki & Duke, 1994). Targets were paid $15 for one hour of participation. We recruited 30 targets, but seven failed to complete the entire study due to user-error recording video responses so these targets contained no videos that could be used leaving 23 target videos and associated network characteristics.

Procedure. Targets began by completing a standard egocentric network survey—in other words, a self-reported social network surrounding the "ego" (i.e., the self; Burt, 1984; Freeman et al., 1987). Next, targets were video-recorded answering five open-ended questions unrelated to social networks, accuracy, or any topic related to the research question (e.g., Colvin, 1993; Funder, 1987, 1995). Responses varied in length from 1 min, 3 s to 2 min, 5 s. The five open-ended questions were: (1) "How would you describe yourself?"; (2) "Can you describe how you like to cook or prepare eggs for yourself or others?"; (3) "Do you have

[3] Additionally, studying people's acquaintance networks would have made data collection more challenging because participants would have to answer more questions about each acquaintance named (Burt, 1984), and the research study was already over an hour long.

[4] To reduce variation in accuracy stemming from possible differences in perceivers' ability to read social cues across racial and ethnic groups, we recruited only white participants as targets. All participants self-identified as female or male unless otherwise noted; the option of "other/non-binary" was provided. In Study 3, we test perceivers' ability to detect social network characteristics using a target sample with racial and ethnic diversity.

any advice about how to best prepare for a job interview?"; (4) "Imagine that scientists found life on 3 other planets! Elon Musk, the CEO of SpaceX, is now selling reasonably priced tickets on daily shuttles to other planets. Passports are being issued for travel into space. What do you do?"; and (5) "Some people say that the best leaders are the ones that don't want to lead at all. What do you think about that?" (Table 2 lists sample responses). To standardize the video presentation time for each target, the first twenty seconds of each target's response to each question was extracted and combined to create a 100-second montage for each target (Ambady et al., 2000; Carney et al., 2007). Targets also completed the Big Five Inventory: 44 items that measure the five core personality traits of extraversion, agreeableness, openness, conscientiousness, and neuroticism (John et al., 2008). Participants concluded by providing demographic information, including their subjective social status (Singh-Manoux, Adler, & Marmot, 2003). Social status was not analyzed; future researchers may wish to do so.

3.2. Target materials (survey)

Network size. We measured network size with a standard name-generator question (i.e., a question that generates names of one's network contacts; Burt, 1984): "From time to time, most people discuss important matters with other people. Looking back over the last six months, who are the people with whom you discussed matters important to you?" Targets could list up to eight contacts.[5] The total number of contacts listed served as our measure of network size (Marsden, 1987, 1988). Notably, this question tends to elicit one's closer network contacts, who tend to be more accessible in memory, rather than their weaker ties, whom targets may interact with less frequently (Fischer, 1982; Marsden, 1987; McPherson et al., 2006).

Proportion male ties. Participants reported the gender (male or female) of each person named on the standard name-generator question above. We measured the proportion of male (vs. female) ties by dividing the number of male contacts from the number of total contacts reported.

Proportion family ties. Participants indicated their relationship to each person named on the standard name-generator question with one of five choices (spouse, other family member, friend, professional contact, or other). Proportion of family ties was measured as the number of family contacts ("significant other" and "other family members") divided by the number of total contacts reported (Marsden, 1987).

Interconnectedness. Participants were presented with a matrix with the same row and column headings consisting of the contacts they named in the name-generator question. Participants could then indicate which pairs of contacts listed had a relationship. This indicated how interconnected their contacts were with other contacts, a measure of the extent to which a person has an interconnected (vs. expansive) network. We measured interconnectedness using network density, where the numerator was the total number of ties between alters present and the denominator was the total number of possible ties between alters ($n(n-1)/2$, in an undirected network).[6]

Table 2
Examples of thin-slice video transcripts (targets' responses) relevant to Studies 1, 2a, and 2b.

How would you describe yourself?

- "I guess I'm a pretty open-minded person, so like I'm willing to try new things. Uhm.. I'm not closed off. Uhm, but I can be pretty quiet sometimes, like in class I'm pretty shy. Uhm, but like, I guess, once you get to know me, I'm like able to talk more. Uhm I like to have fun but…"
- "How would I describe myself? I would describe myself as smart, fun, funny. I enjoy the outdoors and being active. I'm athletic. I'm curious about the world. I like exploring different things, seeing new things. Uhm, I'd also describe myself as laidback."
- "I am a person who has a lot of different kind of interests. Uhm, rather than kind of having like one thing that I'm all about. I, uhm, I'm very interested in a lot of different things. Uhm, I tend to be a pretty independent…"

Can you describe how you like to cook or prepare eggs for yourself or others?

- "Uhm, I like my eggs scrambled. So, I guess, I just, like, crack the eggs and put them in with milk and butter and cheese and salt and pepper and I just scramble them? Cook them over the fire. And I guess, uhm, whenever I eat them, I like to like kind of make them look sort of artsy so I put a little…"
- "I have two ways that I like to cook eggs usually. Uh, either scrambled or fried. Scrambled, uh, I crack two eggs into a bowl and, uh, scramble them in the bowl. Maybe add a little bit of cheese or some milk and then cook in a frying pan."
- "So, I'm actually a really bad cook and I don't like eggs. Uhm, but I do have a story, I am a really bad cook as I said and when I was in high school I was trying to – I was at home alone a lot – and I was trying to kind of, uhm, teach myself how to cook a little. So I decided to try and make scrambled eggs. Uhm…"

Do you have any advice about how to best prepare for a job interview?

- "I guess the best advice I would give would be like don't go in with the mindset that it is an interview for a job. Go in with the mindset that you are basically, you're just talking to someone. You know, someone important, someone that you might wanna meet anyway. So its almost just like you are having a conversation, and I think that's the best way you can like really show who you are and…"
- "Preparing for a job interview, uh, important to research the company, understand, uh, what they are looking for, uh, in an applicant, know what the company does, what their values are, what their mission is. Uhm, try to find out who is going to be interviewing you and learn some things about…"
- "I don't have a whole lot of job interview experience. Uhm, but, in my little experience that I have had, in my few job interviews, the best things for me have been to be confident. Uhm, even if you don't feel confident. Uhm, its to appear confident. And also to be really friendly. I …"

Imagine that scientists found life on 3 other planets! Elon Musk, the CEO of SpaceX, is now selling reasonably priced tickets on daily shuttles to other planets. Passports are being issued for travel into space. What do you do?

- "So if scientists found life on other planets and they have daily shuttles to them, I'd probably treat them just like any other country. So, like, I would love to go – just because I like traveling and I like, you know, seeing new things. But I don't know if I would just jump in my bags right now and go."
- "Wow, life on other planets. What would I do? Uhm, I think I would be interested but honestly I would consider all of the risks of space travel. I'd want to know how safe it was and I'd want to know, uh, how long we would be going for. Uh, it says daily shuttles…"
- "Obviously, I'm going to go out to space. Uhm, I, its kind of been a dream of mine for a long time. Especially to meet other life forms on other planets. I would absolutely love that. Uhm, that would be like the big …

Some people say that the best leaders are the ones that don't want to lead at all. What do you think about that?

- "I, I think that is probably true. Uhm, well, I don't know. I mean, I guess to be a leader you have to have some sort of initiative, uhm, and if you don't want to lead chances are you won't or you won't lead as well. So I can see why that might not be true. But I guess at the same time…"
- "Uhm, I think that some times that can be the case. Uhm, I think leaders aren't leaders until they have people who want them to lead. You can't be a leader by yourself. You need people who want to be led. Uhm, and I guess…"
- "I definitely agree with that thing about, uhm, leaders. I personally am not…I … I do enjoy leading but I also don't think of myself as a leader type person and I…"

Note: All typos and grammatical errors were verbatim extractions from targets' responses.

3.3. Phase 2 method (collecting perceivers' judgments of targets)

Participants. A non-overlapping sample of three hundred and eighty one participant perceivers at a West Coast university participated in an approximately one-hour study in exchange for $15. Six participants did not finish the session (because it took longer than one hour and they experienced delays loading target videos) and were therefore excluded

[5] Only four of the 23 targets in our study reached the limit of eight when naming their contacts.

[6] We also used UCINET to measure interconnectedness using Burt's (1992) standard measure of constraint: (1) $C_i = \sum_j c_{ij}$, $i \neq j$ where C_i is network constraint on target i, and c_{ij} is a measure of i's dependence on contact j. (2) $c_{ij} = (p_{ij} + \sum_q p_{iq} p_{qj})^2$, $i \neq q \neq j$ where p_{ij} is the proportion of target i's social network invested in contact j, $p_{ij} = z_{ij} / \sum_q z_{iq}$, and z_{ij} measures the strength of connection between contacts i and j. Constraint varies with network size, constraint, and hierarchy. Greater constraint indicates that a person is more invested in a tightly knit community, making it more likely that people in their network have redundant information. The results were substantively similar across all studies when interconnectedness was operationalized as constraint.

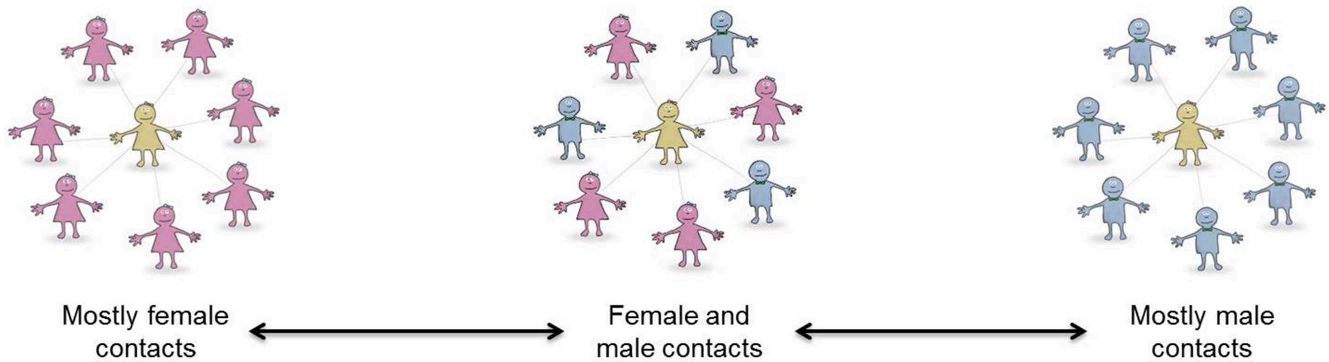

Fig. 1. Visual Social Network Scale to Rate Network Gender Composition (Used by Perceivers). Note: The scale endpoints ranged from 0 (*Mostly female contacts*) to 100 (*Mostly male contacts*).

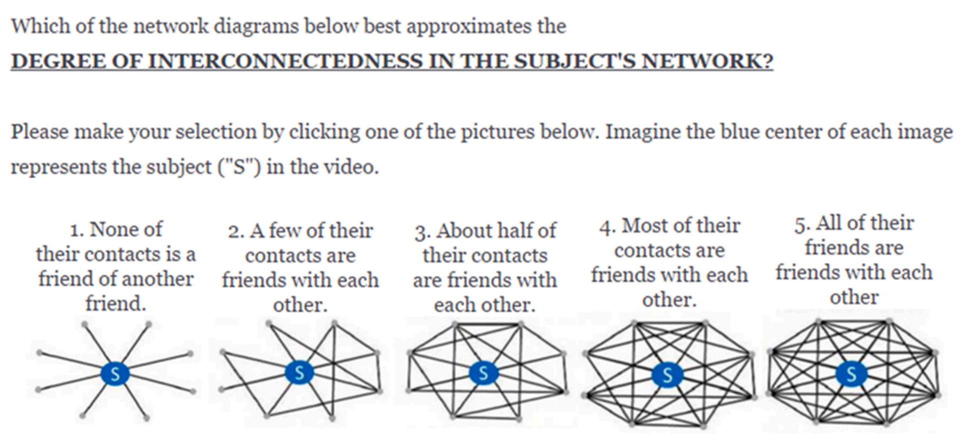

Fig. 2. Visual Social Network Scale for Interconnectedness (Used by Perceivers). Note: The scale endpoints were from 1 (*None of their contacts is a friend of another friend*) to 5 (*All of their friends are friends with each other*).

from analyses, resulting in a final sample size of $N = 375$ perceivers (36.5% male, 63.5% female; $Med_{age} = 21$, $SD = 3.3$; 58% Asian, 35% White, 10% Latinx, 2% Black and/or African American).[7] We used a power analysis setting α to 0.05, effect size r to 0.15, and power to 0.80. This suggested we needed at least $N = 343$ perceivers; we oversampled to be closer to α to 0.01.

Procedure. After observing each target video, perceivers made judgments about each target's social network characteristics. To reduce the cognitive burden on perceivers, we used visual network scales wherever possible (see survey items below; Mehra et al., 2014). Furthermore, to reduce participant fatigue, given time constraints, and following Carney et al. (2007), perceivers viewed and made judgments about a subset of approximately six targets; targets were randomly assigned to bundles of five or six (because of the odd number of targets; $N_{targets} = 23$). The order in which each participant observed target videos was also randomized.

Network size judgment. Perceivers were shown the same name-generator question as targets were shown in Phase 1 and asked to predict the number of people that targets listed in response to the question, which ranged from 1 to 8.

Proportion male ties judgment. Using a visual network scale, perceivers were asked to predict the proportion of the male (vs. female) ties in each target's network; for ease, this was displayed as a percentage on a continuous 100-point scale (0: mostly female contacts, 50: equal numbers of female and male contacts, 100: mostly male contacts; see Fig. 1).

Proportion family ties judgment. Perceivers were presented with three categories of relationships (family members, social friends, and work/professional friends) and asked to predict the relative percentage of each category. The total percentage across all three categories had to equal 100. We measured the judgment of proportion of family ties with the percentage of contacts estimated to be family members.

Interconnectedness. Using a visual network scale, perceivers were asked to predict the interconnectedness of the target's network (1 = *none of their contacts is a friend of another friend*, 5 = *all of their friends are friends with each other*; see Fig. 2). For our analysis, we transformed the visual network scale to network density values using the same formula from Phase 1 (where the numerator was the total number of present ties between alters and the denominator was the total number of possible ties between alters (n(n-1)/2), in an undirected network).

Perceived personality ratings. To compare accuracy about social network characteristics to accuracy about judging the Big 5 personality traits, which prior studies have shown is possible (e.g., Carney et al., 2007), we asked participants to rate each target's perceived Big 5 factors of personality (TIPI; Gosling et al., 2003) to benchmark any findings to accuracy about personality.

Assessing accuracy. Accuracy was operationalized as the correlation between a vector of each perceiver's judgments about a particular network characteristic across targets and the vector of targets' actual criterion data about the same network characteristic. Using profile correlations (a procedure widely used in accuracy research; e.g., Back & Nestler, 2016; Carney et al., 2007; Judd et al., 1991; Krendel et al., 2013; Rule et al., 2013), we computed mean perceiver accuracy scores across perceivers for each of the four social network characteristics—size,

[7] In all studies, the sum for race/ethnicity is greater than 100 because participants were able to select multiple categories.

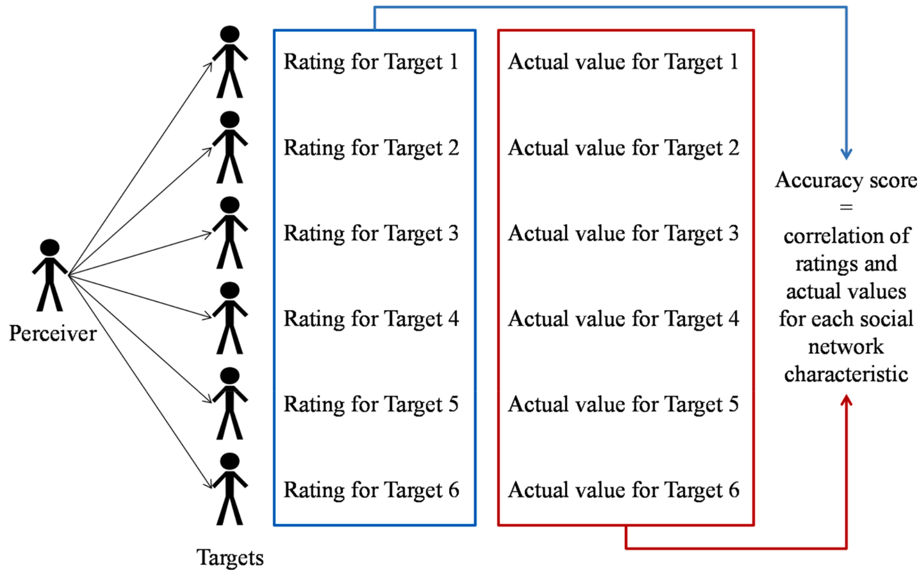

Fig. 3. Visual Representation of Analytical Approach: The Profile Correlation Method of Assessing Interpersonal Accuracy.

gender composition, family composition, and interconnectedness—as well as for accuracy about personality. In this context, Pearson's correlation coefficient *rs* above 0 indicate accurate judgment, below 0 indicate inaccurate judgments, and 0 indicates neither accurate nor inaccurate judgments. As is typical with the Pearson's correlation coefficient, r ranges between -1 (perfect inaccuracy) to 1 (perfect accuracy). Prior studies indicate the level of accuracy often ranges between 0.10 and 0.30 across personality traits and contexts (e.g., Back & Nestler, 2016; Kenny, 1994). After the Pearson's correlation coefficient (r) between perceivers' judgments and targets' criterion scores were calculated, r was converted to Fisher's r for statistical tests and then converted back to Pearson's r for presentation (Carney et al., 2007; see Fig. 3). We conducted one-sample t-tests on each network characteristic to ask whether the mean of perceivers' accuracy scores for different social network characteristics were greater than zero.

3.4. Results and discussion

Accuracy at detecting social network characteristics. Consistent with our predictions, perceivers accurately judged others' network size, $r = 0.09$, $t(365)$[8] $= 3.92$, $p < .001$, proportion of family ties, $r = 0.07$, $t(374) = 3.39$, $p < .001$, and proportion of gender ties, $r = 0.33$, $t(374) = 17.23$, $p < .001$, at zero acquaintance. Perceivers, however, were not accurate at judging network interconnectedness, $r = 0.03$, $t(366) = 0.92$, $p = .360$.

These findings provide the first evidence that people can make accurate social network judgments about strangers based on the briefest exposure to 100 s of social behavior—for example, when deciding whom to ask for directions at the train station or with whom to chat at a networking event. Also, people were not able to make accurate judgments about the interconnectedness of targets' reported contacts.

The relation between accuracy about social network characteristics and accuracy about personality. It is important to note that the Pearson r social network accuracy estimates reported above may be under-estimates; for comparison, Table 3 reports accuracy coefficients of Big Five personality characteristics—all of which were lower than is typically found in the literature (see e.g., Carney et al., 2007). For example, extraversion typically yields coefficients in the $r = 0.22 - 0.55$ range (e.g., Carney et al., 2007). Here, we observe an accuracy coefficient of a mere $r = 0.13$.

Therefore, the effect sizes detecting social network characteristics were small (between $r = 0.07$ and $r = 0.33$) but highly statistically significant, although smaller in magnitude than accuracy about the Big 5 factors of personality, some of which are typically stronger (Borkenau & Liebler, 1993; Carney et al., 2007; Funder, 1999; Hall et al., 2008; Kenny, 1994; Kenny & West, 2010). For example, accuracy about percentage of family ties and network size ($rs = 0.07$ and 0.09, respectively) was roughly comparable to accuracy about a target's extraversion ($r = 0.13$); accuracy about extraversion is typically much higher, which suggests that some of the targets used in Study 1 may not have been particularly expressive, thus reducing accuracy. We attempted to untangle this potential issue in Studies 2a and 2b.

Overall, Study 1 demonstrated that perceivers could make accurate inferences at zero acquaintance about the size and composition (gender; family) of a target's social network but not about interconnectedness among target's contacts. In Studies 2a and 2b, we seek to test the replicability of the social network accuracy effects observed in Study 1. We also develop a new tool for researchers, the Social Network Accuracy Test (SNAT), a freely available assessment tool for investigating questions about accuracy in social network perception.

4. Study 2a

In Study 2a, we attempt a conceptual replication of Study 1. Because Study 1 potentially underestimated the magnitude of the accuracy coefficients, we attempted to use the "best" ten target individuals as stimuli (as explained in depth in the Method section below). In addition,

Table 3
Accuracy of Perceivers' Judgments of Targets' Personality in Study 1.

Target Attribute	Mean Pearson *r*	*N*	Pearson *r* 95% CI
Extraversion	0.13***	374	0.08–0.18
Agreeableness	0.22***	374	0.18–0.27
Conscientiousness	0.23***	373	0.18–0.27
Emotional Stability (Neuroticism)	0.19***	369	0.15–0.24
Openness	-0.04	373	−0.08–0.00

Note: See Table S1 in Supplemental Materials for correlation table of all variables in Study 1.

[8] If a perceiver provided the same judgment value for a social network characteristic across targets, we were unable to calculate an accuracy score for that social network characteristic (due to a lack of variance). For this reason, the degrees of freedom vary slightly across social network characteristics in Studies 1, 2a, and 2b.

we wanted to test the validity of a short individual difference test of social network accuracy that could be administered to participants in less than an hour (the SNAT).

4.1. Method

Participants. 212 participant perceivers (51.2% male, 48.8% female; Med_{age} = 21, SD = 2.6; 50% Asian, 30% White, 6% Mixed, 5% Latinx, 3% East Indian, 2% Black and/or African-American, 2% Other) were recruited from a West Coast university and received partial course credit in return for participation. The sample size was determined by the number of students enrolled in an introductory organizational behavior class; all students in the class were invited to participate.

Procedure. The procedure and survey materials were the same as in Study 1, with the following exception: all perceivers made judgements about the same ten targets (presented in a randomized order) instead of a subset of 5–6 targets from the full set of 23 targets. Because the accuracy coefficients in Study 1 were small (but statistically significant) for social network accuracy and even for extraversion, which typically yields coefficients in the $r = 0.22 – 0.55$ range (e.g., Carney et al., 2007), we were concerned that Study 1 underestimated all accuracy coefficients observed, including the social network accuracy coefficients. Thus, we selected ten targets on the basis that perceivers in Study 1 were especially accurate in assessing social network characteristics of these targets. This approach suggested these targets are "good targets" (Colvin, 1993; Funder, 1995; Kenny, 1994); in other words, these 10 targets, according to Funder's (1995) RAM, were sufficiently expressive to allow for accuracy to occur. As in Study 1, we calculated perceivers' average judgment for each target's four social network characteristics. We used this to calculate the absolute value of the judgment error, or the difference between targets' actual social network characteristic and perceivers' average judgment (in other words, the target's "readability" for each social network characteristic). For each social network characteristic, we selected the top two targets with the smallest average judgment error (across all perceivers) to capture the most "readable" targets. For gender and family composition, we selected the top four targets with the smallest average judgment error, which included two targets that were highly readable in both dimensions (total of six targets selected). All targets selected for the SNAT had above average readability (i.e., smallest absolute value judgment error across all four social network characteristics).

4.2. Results and discussion

Consistent with Study 1 and our predictions, perceivers accurately detected social network size, r = 0.12, $t(211)$ = 5.61, $p < .001$, proportion family ties, r = 0.18, $t(211)$ = 9.18, $p < .001$, and proportion gender ties, r = 0.46, $t(211)$ = 25.58, $p < .001$. These accuracy coefficients were, indeed, stronger than those observed in Study 1. However, for interconnectedness, perceivers were systematically *in*accurate, r = -0.15, $t(210) = -6.57$, $p < .001$, suggesting a possible discrepancy between the cues perceivers *think* are associated with interconnectedness and the cues that are *actually* associated with interconnectedness. This result is similar (both in theory and phenomenon) to the finding from the lie-detection literature that people believe incorrectly that averting one's eye contact is a sign of deception. When perceivers use this cue, as they often do, they are less accurate lie detectors (DePaulo et al., 2003). Moreover, judging the interconnectedness of a person's social network is related conceptually to judging how honest, forthright, or psychologically healthy a person is. People with highly interconnected social networks tend to be psychologically healthier and to have less psychopathology (Berkman & Glass, 2000; Litwin, 2003; Litwin & Shiovitz-Ezra, 2006), which is associated with less deception. Specifically, when one tells a lie in a highly embedded social network, it is not long before everyone in the network is aware of the transgression; thus, people who tend to engage in deception have less interconnected social networks where none of their social ties know any of their other social ties.

In summary, Study 2a both replicates and extends the results from Study 1 by demonstrating that perceivers can make accurate inferences about others' social network size, gender, and family composition at zero acquaintance using the SNAT. The accuracy coefficients were not much larger in Study 2a than in Study 1; therefore, we conclude that the size of the accuracy coefficients are likely small but robust. However, the SNAT appears to be a reliable and robust indicator of social network accuracy. The focus of Study 2b was to attempt a direct replication of Study 2a and provide some preliminary validity information for researchers interested in potentially using the SNAT.

5. Study 2b

The goal of Study 2b was twofold: (1) to conduct an exact replication of Study 2a and (2) to provide preliminary validity data for the SNAT. We did not seek to systematically examine the SNAT's convergent and discriminant validity; instead, we measured a few individual difference measures, including an emotion-detection task, to situate individual differences in the SNAT within a preliminary nomological network of constructs, such as the Big 5 factors of personality, impression-management concern, gender, and emotion-detection accuracy. Past research has shown that women (vs. men; e.g., Hall, 1984) and individuals low (vs. high) in emotional stability (e.g., Denissen & Penke, 2008) are more accurate at detecting emotion, threat, personality, and other characteristics. Taken together, it made sense to ask whether the Big 5 characteristic of neuroticism (the opposite of emotional stability) predicted accuracy on the SNAT. There is also a small but consistent gender difference in accuracy, such that women are slightly more accurate than men when judging emotion (Hall, 1984); thus, we expected to possibly find a gender effect on the SNAT. Lastly, consistent with previous research on the (lack of) intercorrelations between various task-based measures of accuracy in social perception (e.g., Hall et al., 2017, 2018; Schlegel et al., 2017), we expected a low or null correlation with other assessments of interpersonal perception abilities, such as emotion-detection ability (as well as low intercorrelations among the four social network accuracy indices).

5.1. Method

Participants. 272 participants (50.4% male, 49.6% female; Med_{age} = 20, SD = 1.8; 46% Asian, 26% White, 8% Latinx, 7% Other, 5% Mixed, 4% Black and/or African American, 3% East Indian) were recruited from a West Coast university and received partial course credit in return for participation. As in Study 2a, the sample size was determined by the number of students enrolled in an introductory organizational behavior class; all students in the class were invited to participate.

Procedure. The procedure and survey materials were exactly the same as in Study 2a, except that we additionally measured the following individual differences: impression management (BIDR; Hart et al., 2015; Paulhus, 1984; α = 0.74; 1 = *not true*, 7 = *very true*), Big 5 factors of personality (TIPI; Gosling et al., 2003; 1 = *disagree strongly*, 5 = *agree strongly*), and emotion detection accuracy (DANVA; Nowicki & Duke, 1994). Because we collected these measures at different time points from the SNAT, 23 participants are missing personality scores for the Big 5 (an additional participant is missing scores for agreeableness).

5.2. Results and discussion

Again, consistent with Studies 1 and 2a, perceivers were accurate at detecting social network size, r = 0.12, $t(267)$ = 6.88, $p < .001$, proportion family ties , r = 0.16, $t(271)$ = 8.74, $p < .001$, and proportion gender ties, r = 0.50, $t(271)$ = 33.55, $p < .001$. These data provided additional evidence that people can make accurate judgments about these social network characteristics of strangers based on merely about

Table 4
Means, standard deviations, and correlations between the overall SNAT and the sub-scales for accuracy (with confidence intervals) in Study 2b.

Accuracy Variable	*M*	*SD*	1	2	3	4
1. SNAT Composite	0.00	0.51				
2. Network Size	0.12	0.28	0.55** [0.46, 0.63]			
3. Prop. Gender	0.50	0.20	0.58** [0.49, 0.65]	0.11 [−0.01, 0.23]		
4. Prop. Family	0.16	0.29	0.55** [0.46, 0.63]	0.06 [−0.06, 0.18]	0.17** [0.05, 0.28]	
5. Interconnectedness	−0.19	0.31	0.35** [0.24, 0.45]	−0.06 [−0.18, 0.06]	−0.12* [−0.24, −0.00]	−0.12* [−0.24, −0.00]

Note. M and *SD* represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

100 s of video-recorded information. Again, perceivers were systematically *in*accurate when judging interconnectedness, $r = -0.19$, $t(269) = -9.64$, $p < .001$—further supporting the idea that, as in lie-detection research, perceivers may have the opposite belief about how a person with a more interconnected social network behaves.

Table 4 reports the intercorrelations between the overall SNAT composite index (variables standardized then averaged) of "overall network accuracy" as well as each of the four sub-scales. Consistent with past research on interpersonal accuracy, which has found accuracy about one domain to be largely orthogonal to, or very slightly correlated with, accuracy about another domain (e.g., accuracy about extraversion does not correlate with accuracy about openness; Hall et al., 2017, 2018; Schlegel et al., 2017). Accuracy about the four network characteristics were largely unrelated. These findings are consistent with over 100 years of research (beginning with E. L. Thorndike in the 1920 s; Thorndike, 1920) demonstrating that even when the method of measurement is held constant, there seems to be no "G" or "general intelligence" factor when it comes to social judgment accuracy.

Table 5 reports the beginning of a nomological network for the SNAT. The overall score and each of the four sub-scales is presented, as each relates to a number of demographic and personality variables. On balance, the SNAT and its subscales were not related to gender identity (male/female; a finding inconsistent with Hall, 1984 and our prediction; however, gender differences are found only for accuracy in emotion detection), impression management, emotion detection (which, was expected), extraversion, agreeableness, conscientiousness, emotional stability (also inconsistent with our hypothesis), and openness to experience.

Interestingly, higher accuracy about network size was related to lower levels of impression management, $r(266) = -0.18$, $p = .003$. This is likely a false-positive finding, given the number of correlations presented and the fact that this is the only statistically significant finding. Intuitively, the opposite would make sense—that the most "careerist" or "social-climbing" individuals would be more sensitive to the potential value of another person's network—but that is not what we found.

These data are not meant to offer a comprehensive convergent and discriminant validity profile for the SNAT. Rather, they present very preliminary evidence that the individual differences in assessing social network accuracy (measured with our scale, the SNAT) are not merely a measure of emotion-detection accuracy or an index of personality. Study 2b demonstrated total replicability of Studies 1 and 2a and some discriminant validity for the 10-item SNAT. The SNAT video stimuli and all criterion data (e.g., demographics, raw social network data) are freely available for academic use (https://osf.io/zgbse).

Overall, the evidence from 859 perceivers across Studies 1, 2a, and 2b is the first to demonstrate that perceivers can accurately detect network size, gender, and family composition, but not interconnectedness, after watching thin-slice videos of ordinary people engaging in routinely expressive behaviors for about 100 s. Given that all three studies reported thus far used a paradigm in which perceivers watched videos of targets engaging in routinely expressive behavior for less than two minutes, in Study 3, we tested whether perceivers could accurately judge social network characteristics after a demanding dyadic business interaction: a negotiation. Study 3 allowed us to substantially increase the number of targets and explore which perceptual cues about targets facilitated perceivers' judgmental accuracy.

6. Study 3

Study 3 has three goals. The first is to test the hypotheses on a much larger and more diverse set of targets. The second is to test whether the effects observed in Studies 1, 2a, and 2b generalize to a negotiation task more realistic of typical organizational life, in which people are engaged in a demanding task and not necessarily paying attention to the social network characteristics of their interaction partner. The third is to attempt to identify how accurate judgments were possible by examining the role of theoretically relevant social-behavioral tendencies and traits (see Table 1). Notably, accuracy in live, face-to-face interactions is not a commonly used methodology because it is difficult to conduct and accuracy is difficult to achieve (Ickes, 1993). However, to test whether our results would replicate in the "real world," we conducted Study 3 with the same hypotheses tested in Studies 1, 2a and 2b.

6.1. Method

Study 3 was preregistered (https://aspredicted.org/ri987.pdf).[9]

Participants. Our preregistration plan specified that we would recruit as many participants as possible from two undergraduate required leadership classes taught as a part of a business school curriculum. In total, 686 individuals (343 dyads) from two universities (one on the West Coast and one on the East Coast) participated in exchange for course credit (48.8% male, 50.9% female, 0.3% other/non-binary/non-identified; $Med_{age} = 20$, $SD_{age} = 2.05$; 57% Asian, 34% White, 8% Latinx, 2% Black and/or African American).

Procedure. Prior to the beginning of the semester (weeks before the study), participants completed a pre-survey containing the in-depth social network measures from which we extracted the same four characteristics used in the previous studies: social network size, gender and family composition, and interconnectedness. Then, at the beginning of the study, we randomly assigned participants to be partners in a negotiation simulation called "Rio Copa Foods" (Bontempo & Iyengar, 2008; used in prior research: e.g., Park et al., 2013; Ronay & Carney, 2013).

[9] Note that we made two deviations from our preregistration. First, we preregistered that we would control for the target's Big 5 personality and gender in a robustness analysis. We have now re-theorized that these variables serve as mechanisms (i.e., cues to make accurate judgments) and thus do not report robustness tests with these variables as covariates. Second, we preregistered that we would explore the explanatory mechanism for our predicted finding with bootstrapped mediation models. We decided instead to explore mechanisms with Brunswik's (1956) lens model due to concerns that a multiple-mediator model with 14 mediator variables would suffer from multicollinearity.

Table 5
Means, standard deviations, and correlations between the SNAT, sub-scales and personality/demographic variables (with confidence intervals) in Study 2b.

			Accuracy Variables				
Variable	*M*	*SD*	SNAT Composite	Network Size	Gender Composition	Family Composition	Inter-connectedness
Gender	0.50	0.50	0.01 [−0.11, 0.13]	−0.09 [−0.21, 0.03]	0.07 [−0.05, 0.19]	0.08 [−0.04, 0.20]	−0.03 [−0.15, 0.09]
Impression Mgmt	4.00	0.95	−0.10 [−0.21, 0.02]	−0.18** [−0.30, −0.06]	0.11 [−0.01, 0.23]	−0.09 [−0.21, 0.02]	−0.02 [−0.14, 0.09]
Emotion Detect	0.77	0.11	0.08 [−0.03, 0.20]	−0.02 [−0.14, 0.10]	0.11 [−0.01, 0.23]	0.01 [−0.11, 0.13]	0.07 [−0.05, 0.19]
Extraversion	3.73	0.95	0.06 [−0.06, 0.18]	−0.02 [−0.15, 0.10]	−0.00 [−0.13, 0.12]	0.11 [−0.02, 0.23]	0.04 [−0.08, 0.17]
Agreeableness	3.64	0.79	−0.09 [−0.22, 0.03]	−0.01 [−0.13, 0.12]	−0.09 [−0.21, 0.04]	−0.05 [−0.18, 0.07]	−0.04 [−0.16, 0.09]
Conscientiousness	4.07	0.66	−0.12 [−0.24, 0.00]	−0.11 [−0.23, 0.01]	−0.09 [−0.21, 0.04]	−0.04 [−0.17, 0.08]	−0.00 [−0.13, 0.12]
Emotional Stability	3.84	0.87	0.03 [−0.10, 0.15]	−0.06 [−0.18, 0.07]	0.05 [−0.07, 0.18]	0.05 [−0.07, 0.18]	−0.00 [−0.13, 0.12]
Openness	3.88	0.73	−0.01 [−0.14, 0.11]	−0.07 [−0.20, 0.05]	−0.03 [−0.16, 0.09]	0.09 [−0.04, 0.21]	0.00 [−0.12, 0.13]

Note. *M* and *SD* represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Participants were randomly assigned to the role of either President and majority stockholder of the company under acquisition consideration or Vice President of Business Development for the potential purchasing company. Participants received confidential role information and were instructed to attempt to reach an agreement on the sale. Participants were given 30 min to discuss the deal face to face (over teleconference, Zoom; sessions were recorded). The negotiation was realistic, stressful, and cognitively demanding (Akinola et al., 2016). Participants completed the negotiation, on average, in $M = 31.09$ min ($SD = 11.76$ min).

After finishing the negotiation, participants completed a post-negotiation survey in which they judged the social network characteristics of their partner and rated a number of social behaviors related to the four network characteristics (detailed in the fourth column of Table 1) to determine which, if any, target social behaviors statistically explain *how* perceivers were able to accurately assess the network characteristics of strangers. Since participants provided their own standing on the social network variables (assessed through the pre-survey), and we had each person judge their partners' social network characteristics (assessed through the post-survey), participants served as both perceivers and targets in this study; appropriate statistical analyses were used to manage the statistical interdependence.

6.2. Target materials

Social network measures. We used the same *target* social network measures for network size, proportion male (vs. female), proportion family (vs. social friends and academic or work-related professional contacts), and interconnectedness as in Study 1, except that for the gender identity of each contact, participants had the option of selecting Non-Binary. As in Study 1, we still calculated proportion male (vs. female) by taking the number of male contacts and dividing it by the total number of reported contacts male, female, and non-binary contacts.

Demographic information. For each participant, we also collected gender identity, race and ethnicity, and age.

6.3. Perceiver materials

Social network judgments. We used the same judgments of social network attributes as in Studies 1-2b with minor exceptions.[10] Changes included: (1) the network size measure ranged from 0 to 20 instead of 1 to 8; the scale was widened to reflect the additional variation present in the target data ($M = 5.27$ contacts, $SD = 3.67$, $Min = 0$, $Max = 20$). Second, as in the Target Survey, we specified that a family member includes a significant other.

Social behaviors examined as possible explanations for network accuracy. Our literature review, summarized in Table 1, details social behaviors about which perceivers tend to be accurate (e.g., extraversion) and that have been shown to be associated with each of the four network characteristics. On these bases, we assessed perceivers' impressions of interaction partner's social behaviors/traits on the following measures.

Approach orientation. To measure each target's perceived approach orientation, participants completed the following five items: "I think my partner would … ," (1) "go out their way to get things they want," (2) "act on the spur of the moment," (3) "get excited right away when they see an opportunity for something they like," (4) "crave excitement and new sensations," and (5) "be excited to win a contest" (Carver & White, 1994; α = 0.72; 1 = *strongly disagree*, 7 = *strongly agree*).

Big 5 personality. To measure each target's perceived personality, participants judged the target's Big 5 factors of personality (TIPI; Gosling et al., 2003) on a scale from 1 = *strongly disagree*, 7 = *strongly agree*.

Desire for status. To measure each target's perceived desire for social status, participants completed the following three items: "I think my partner … " (1) "does not care about status among peers" (reverse-scored), (2) "is highly concerned with having high social status," and (3) "would be pleased to have a position of prestige and social standing" (Flynn et al., 2006; α = 0.61; 1 = *strongly disagree*, 7 = *strongly agree*).

Likeability. To measure each target's likeability, participants completed the following five items: "On average, I think people (maybe including myself) would … " (1) "like this person," (2) "want to be friends with this person," (3) "want to have a friendly chat with this

[10] We additionally measured whether participants knew each other before the negotiation simulation by asking, "How well did you know your partner before the negotiation?" (1 = *not at all*, 5 = *extremely*). As expected, participants did not know their partner before the negotiation ($M = 1.18$, $SD = 0.60$). Participants were instructed to request reassignment if they were randomly assigned to a partner they already knew.

person," (4) "be able to establish a personal friendship with this person," and (5) "find this person pleasant to be with" (McCroskey & McCain, 1974; α = 0.94; 1 = *strongly disagree*, 7 = *strongly agree*).

Masculinity and femininity. To measure each target's perceived masculinity and femininity, participants completed 15 masculinity items and 15 femininity items from the Bem (1981) Sex-Role Inventory ($\alpha_{masculinity} = 0.89$; $\alpha_{femininity} = 0.83$; 1 = *strongly disagree*, 7 = *strongly agree*).

Need to belong. To measure each target's perceived need for belonging, participants completed the following four items: "I think my partner … " (1) "has a strong need to belong," (2) "wants other people to accept them," (3) "is bothered a great deal when they are not included in other people's plans," and (4) "needs to feel that there are people they can turn to in times of need" (Leary et al., 2013; α = 0.74; 1 = *strongly disagree*, 7 = *strongly agree*).

Opener ability. To measure each target's perceived opener ability (i.e., ability elicit intimate self-disclosure), participants completed the following six items: "I think my partner is … " (1) "a good listener," (2) "very accepting of others," (3) "trustworthy with other people's secrets," (4) "easily able to get people to 'open up,'" (5) "sympathetic to people's problems," and (6) "able to keep people talking about themselves" (Miller et al., 1983; α = 0.85; 1 = *strongly disagree*, 7 = *strongly agree*).

6.4. Results and discussion

While in prior studies, perceivers judged multiple targets (e.g., 10 in Studies 2a and 2b), in Study 3, perceivers only judged one target (i.e., their partner). As a result, we were unable to use the profile correlation method used in the previous studies reported here, which requires perceivers to judge at least three targets to produce a correlation. Thus, to generate an accuracy coefficient comparable to prior studies, we correlated each perceiver's judgment of the target with the target's self-reported network value (i.e., the criterion) across the entire sample (e.g., Murphy et al., 2003). Moreover, in contrast to prior studies, perceivers also served as targets (i.e., judged their partner *and* were judged by their partner), such that the partners were nested within dyads. To account for the nonindependent data, we reported robustness analyses with cluster-robust standard errors (Franzese & Kam, 2009).

Consistent with the previous studies, perceivers were able to reach accurate judgments about another person's social network characteristics in a live interaction, though such judgments were not expected or suggested until after the negotiation was complete and participants could no longer see each other. Again, the results suggested that even in an actual face-to-face Zoom interaction, perceivers drew accurate inferences about network size and composition, but not interconnectedness: size, $r = 0.08$, $t(680)$[11] $= 2.03$, $p = .043$, percentage male ties, $r = 0.38$, $t(660) = 10.52$, $p < .001$, percentage family ties, $r = 0.11$, $t(660) = 2.80$, $p = .005$, and network interconnectedness, $r = -0.04$, $t(635) = -1.04$, $p = .298$.

Moreover, when we accounted for nonindependent data with cluster-robust standard errors, the results remained the same: accuracy detecting network size, $r = 0.08$, $t(660) = 2.06$, $p = .040$, percentage family ties, $r = 0.11$, $t(660) = 2.87$ $p = .004$, and percentage male ties, $r = 0.38$, $t(660) = 11.71$ $p < .001$ were statistically significant and positive, and accuracy detecting network interconnectedness was not statistically significant, $r = -0.04$, $t(635) = -1.12$, $p = .264$.

Drawing on Brunswik's (1956) lens model, we conducted a series of analyses to test (a) the extent to which inferences about the target's social behaviors and characteristics were related to what the target reported about their social network characteristics, and (b) the extent to which perceivers used inferences about the target's social behaviors and characteristics to make inferences about the target's social network characteristics. Juxtaposing the two analyses allows us to determine which social behaviors and characteristics are valid (or invalid) cues leading to accurate (or inaccurate) judgments about others' social network characteristics. The correlations in the left-hand section of Table 6 indicate the relations between the target's self-reported target network characteristics and the perceiver inferences. These "cue-validity" correlations show which perceiver inferences *were actually related* to the target's network characteristics. The "cue-utilization" correlations in the right-hand section of Table 6 reflect the relations between the perceiver's inferences about the target's social behaviors and social network characteristics. These cue-utilization correlations show which behavioral cues perceivers *used* to make judgments about the target's social network characteristics. Cues were sometimes correctly used and sometimes incorrectly used, and at other times, cues that could have been used to facilitate accuracy were ignored.

Network size. Perceivers correctly used a target's perceived agreeableness, extraversion, femininity, likability, gender, and opener ability to make accurate inferences about network size. As summarized in Table 1, we predicted that perceptions related to sociability, such as extraversion,[12] likeability, and opener ability, may facilitate accurate judgments about network size because they are social behaviors that tend to characterize people with larger social networks. Although there is less research suggesting that women tend to have larger networks than men, perceivers may have relied on gendered cues to assess emotional intelligence, willingness to collaborate, and ability to resolve conflict through compromise, which are known to be associated with larger networks. In addition, perceivers also relied on the following cues to make inferences about network size, though these inferences were not related to a target's network size (i.e., incorrect cues): approach orientation, need to belong, and openness. Moreover, while perceived conscientiousness was related to target network size, perceiver judgments of conscientiousness were not related to perceived network size (i.e., conscientiousness was an overlooked cue that could have facilitated accuracy). To the best of our knowledge, past research has not identified a person's conscientiousness as a correlate of their network size. Conscientiousness is highly predictive of a person's level of commitment to social groups, in part because conscientiousness individuals feel a sense of duty and obligation to help groups (e.g., Choi et al., 2015). To the extent that conscientiousness is linked to a sense of duty and obligation to one's core network, it makes sense that conscientiousness also appears to predict network size.

Gender composition. Perceivers correctly used a target's perceived femininity and gender to make accurate inferences about the gender composition of their networks, providing evidence that perceivers correctly expected gender homophily in strangers' egocentric networks. On the other hand, perceivers also used perceived agreeableness, need to belong, and neuroticism to make judgments about the gender composition in a network, when, in reality, these inferences were not related to the proportion of males in a network (i.e., incorrect cues). To the extent that perceivers associated agreeableness, a need to belong, and neuroticism with women, perceivers may have incorrectly relied on

[11] The degrees of freedoms for the four network characteristics vary for the following reasons. For network size, we are missing four perceiver judgments (resulting in $N = 682$). For network proportion male, proportion family members, and interconnectedness, 24 targets reported a network size of 0, so we were unable to calculate target values for those participants resulting in $N = 662$. Moreover, there were an additional 25 targets missing a measure for network interconnectedness because they reported a network size of 1 (interconnectedness is only meaningful for networks with more than 1 social tie), resulting in $N = 637$ for interconnectedness.

[12] It is important to note that while perceivers used cues about extraversion to accurately assess network size, judgments about extraversion were not redundant with judgments about network size. Perceived extraversion and target network size correlated $r = 0.16$, indicating that extraversion only accounts for 2.56% of the variance in target network size. In other words, network size and perceived extraversion are related but distinct constructs.

Table 6
A Brunswik (1956) Lens Model Analysis of Network Judgments: Cue-Validity and Cue-Utilization Correlations in Study 3.

Cue-validity correlations					Cue-utilization correlations			
Target Size	Target Male Prop.	Target Family Prop.	Target Inter.	Cues	Perceived Size	Perceived Male Prop.	Perceived Family Prop.	Perceived Inter.
0.10**	−0.03	−0.01	−0.05	Agreeableness	0.11**	−0.11**	−0.03	0.05
0.04	0.05	−0.09*	−0.02	Approach Orient.	0.14**	0.06	−0.06	0.09*
0.11**	−0.05	0.02	0.02	Conscientiousness	0.03	−0.04	0.07	0.05
0.00	0.06	0.02	0.02	Desire for Status	−0.03	0.02	−0.08*	0.04
0.16**	0.02	−0.08*	−0.05	Extraversion	0.12**	0.02	−0.10**	0.13**
0.08*	−0.13**	−0.02	−0.07	Feminine	0.16**	−0.23**	0.06	0.05
0.09*	−0.02	−0.07	−0.05	Likability	0.14**	−0.04	−0.06	0.10*
−0.14**	0.53**	−0.02	0.18**	Male (d)	−0.12**	0.68**	−0.02	0.02
0.05	0.03	−0.04	0.05	Masculine	0.07	0.10*	−0.01	0.08*
0.02	−0.05	0.01	−0.03	Need to Belong	0.09*	−0.13**	−0.03	0.04
0.00	−0.06	−0.01	−0.03	Neuroticism	−0.03	−0.08*	0.00	−0.10**
0.09*	−0.01	−0.10**	−0.08	Opener Ability	0.21**	−0.07	−0.01	0.08*
0.07	0.01	−0.05	0.01	Openness	0.10**	0.00	−0.06	0.07

Notes: Male Prop. = Male Proportion; Family Prop. = Family Proportion; Inter. = Interconnectedness. Approach Orient. = Approach Orientation. Openness = Openness to Experience. Except for Male (dummy variable), all of the cues are perceiver inferences. * $p < .05$. ** $p < .01$. See data on nonverbal behaviors coded in Table S2 in the Supplemental Materials and the correlation of nonverbal behaviors with network characteristics in Table S3.

these cues to make judgments about the extent of gender homophily in a stranger's network. These incorrectly used cues inform our understanding of how perceivers think about the types of people whose networks contain a larger composition of male ties—people who are less agreeable, have less of a need to belong, and are less neurotic—shedding new light on how gender shapes perceivers' expectations of the nature of social ties with men.

Family composition. Perceivers correctly used a target's perceived extraversion to make accurate inferences about the proportion of family ties in a network, such that: (a) target network size was negatively related to perceivers' inferences about extraversion, and (b) perceivers' inferences about extraversion were negatively associated with their judgments about the proportion of family times in a network. In other words, more extraverted people have a smaller (vs. larger) proportion of family ties, and perceivers correctly used extraversion to infer that the target individual has a smaller (vs. larger) proportion of family ties. In addition, perceivers used desire for status to judge the proportion of family ties, when, in reality, perceived desire for status was not related to a target's proportion of family ties (i.e., incorrect cue). Moreover, while target network size was related to perceiver inferences about approach orientation and opener ability, perceivers did not use these cues to make judgments about the proportion family of family ties (i.e., missed cues that could have been used to facilitate more accuracy). Despite our expectations that perceivers would rely on gender cues to accurately perceive the family proportion of a stranger's network, gender was neither associated with targets' actual networks nor perceivers' accurate judgments about the family composition of targets' networks; thus, the perceived association between women and family interactions may be weaker in university settings, and such gendered cultural beliefs may be changing in society.[13]

Interconnectedness. Consistent with the lack of overall accuracy about network interconnectedness, none of the measured cues were related to either perceived or actual network interconnectedness—in other words, there were no correctly used cues. This finding is consistent with the lack of overall accuracy observed about network interconnectedness. Moreover, perceivers incorrectly thought that a host of cues—approach orientation, extraversion, likability, masculinity, neuroticism, and opener ability—were related to target network interconnectedness. In addition, based on previous research, we expected that women would be associated with greater interconnectedness (Brands & Kilduff, 2014); however, in Study 3, males had a more interconnected network. Thus, given the lack of prior evidence linking men to interconnectedness, we were not surprised that perceivers did not use a target's gender to judge interconnectedness (i.e., missed cue).

Taken together, these results demonstrate that even in an ecologically valid, face-to-face negotiation in which participants were both stressed and cognitively taxed, perceivers were still able to accurately infer the network characteristics of their interaction partner in a manner consistent with the thin-slice lab studies reported in Studies 1, 2a, and 2b. These data reveal that the accuracy effects reported here are replicable, reliable, and generalizable, and that any effects observed using the SNAT can likely be trusted, as they are consistent with data harvested using a completely different, real-world, face-to-face paradigm.

7. General discussion

Across four studies using multiple paradigms, 1545 perceivers, and a variety of samples, we demonstrated through both exact and conceptual replications (the last of which, Study 3, was pre-registered) that perceivers can accurately detect the size and composition (gender, family) of a stranger's social network. We also found evidence that perceivers cannot accurately judge a stranger's network interconnectedness. This set of studies is the first of its kind, of which we are aware, to demonstrate people's ability to accurately judge some of the most critical aspects of a stranger's social network. We also provide the SNAT—an individual difference measure that assesses the ability to accurately detect social network characteristics. In so doing, we have made available target videos and untested social network characteristics (e.g., racial composition) that we hope will enable future researchers to test additional hypotheses about social network accuracy.

7.1. Theoretical contributions

Theories of network advantage posit that those who understand how and to whom people are connected reap support, status, information, and even financial benefits from this knowledge (Burt, 2004, 2007; Burt & Ronchi, 2007; Dunbar, 2008; Mehra et al., 2006). Such advantages hinge on the ability to accurately read others' networks. When deciding whether to connect with someone who can give valuable career advice, or to avoid someone who is central in a conflict, one needs to accurately identify network characteristics of unknown others. To our knowledge, this study provides one of the first direct tests of common assumptions

[13] We also note that our target samples were primarily comprised of white or Asian participants, which limited ethnic variation that could have been associated with judgments about family composition of targets' network. As we discuss in the General Discussion, future research would benefit from a more thorough investigation of how social network accuracy varies depending on the racial/ethnic identification of the target individual.

underlying social network tie formation, focusing on the network characteristics of unfamiliar others. We focus on commonplace judgments about others' social worlds because "behind them lies the whole social order" (Bourdieu, 1984: p. 468). Our results indicate that information about a person's network size and composition can likely be accurately conveyed to, and modestly detected by, perceivers; however, information about the interconnectedness of a person's network cannot likely be accurately perceived by others.

The findings from this study also make at least two theoretical contributions to social psychology and organizational behavior. First, the research contributes to the thin-slice research paradigm by introducing the ability to thin slice others' social network characteristics (e.g., Ambady et al., 2000; Ambady & Rosenthal, 1992; Carney et al., 2007; Weisbuch & Ambady, 2011). Research on person perception in social psychology shows that people can make remarkably accurate judgments about a variety of personal characteristics, such as another person's emotions, thoughts, feelings, traits, and characteristics, such as sexual orientation, Big Five personality dimensions, religious identification, and political orientation (e.g., Alaei & Rule, 2016; Allport & Kramer, 1946; Ambady et al., 1999; Carney et al., 2007; Funder, 1995; Hall et al., 2016). The findings reported here demonstrate that people can also accurately strangers' complex and hidden (to the observer) behavioral and social tendencies—the architecture of their *social networks.* In doing so, this research provides evidence of the micro-foundations of social judgment accuracy underlying many prominent sociological theories of social interaction, ranging from Bourdieu's (1984) construct of the habitus to Goffman's (1959) account of impression management.

Second, these findings suggest that social-behavioral tendencies play a role in routine social network judgments prevalent in organizations (Barsade, 2002; Bazerman & Moore, 2013; Hodgkinson & Healey, 2008; Jost, Federico, & Napier, 2009; Ziegert & Hanges, 2005). For example, previous research demonstrates that accurate detection of nonverbal behavior is related to leadership ability (Ronay & Carney, 2013) and negotiation outcomes (Elfenbein et al., 2007). Other research suggests nonverbal behaviors are critical to maintaining hierarchical arrangements of power and status in the workplace (e.g., Hall, Coats, & LeBeau, 2005; Locke & Anderson, 2015). However, future research is needed to investigate the relationship between social network judgments and organizational outcomes.

7.2. Practical contributions

Our findings about the accuracy of judgments about strangers' social networks lead to several practical prescriptions. First, our results demonstrate that some people have the skill to accurately "see" into another's social network based merely on a brief initial encounter by relying, in part, on social behaviors. This "skill" may be one that can be improved upon by training perceivers about which cues to use when making social network judgments. Previous research on organizational networks uncovered evidence that employees and leaders who have the ability to accurately detect organizational networks reap advantages within the organization (Casciaro, 1998; Casciaro et al., 1999; Krackhardt, 1990). Our study extends this work by uncovering evidence that accurate detection of *strangers'* networks can occur and raises possibility of reaping further advantages from this social judgment skill. For jobs that are heavily dependent on the social networks of unfamiliar others, such as sales or leading expansion into new markets, employees who, for example, can accurately detect the size of unknown others' social network might gain a competitive advantage. Furthermore, social network accuracy could position new organizational entrants to quickly identify where and through whom valuable social connections can be activated. More broadly, those with the ability to accurately judge others' social network characteristics may gain advantages in hiring decisions (Rivera, 2012), venture capital funding (Huang & Knight, 2017), financing and investment decisions (Shane & Cable, 2002), courtship and mate selection (McFarland et al., 2013), or targeted organizational interventions (Banerjee et al., 2014; Paluck et al., 2015). At a time when public health officials and organizational managers are aiming to prevent the spread of a global pandemic, accurately judging which unfamiliar others may have close networks with a greater proportion of family members, which could increase their risk of transmission, may facilitate the design of reopening policies.

The fact that naive perceivers, blind to the study aims and with minimal context and interaction, were able to accurately detect people's social network characteristics suggests that this skill can be scaled and automated using machine learning models. To what extent can thin slices harvested from digital and online video platforms be used to accurately assess the characteristics of a person's circle of confidantes? Accurately predicting people's social network characteristics might be used to improve numerous campaigns, products, and services. For instance, political strategists might more optimally target specific voters on issues such as abortion, marriage, or contraception policies based on the family or gender composition of their close networks. Useful information could be inferred from publicly available video/audio content (e.g., YouTube, Instagram, TikTok, Clubhouse) that provides thin slices of their behavior. However, this predictive ability could have negative implications, because it can be obtained without consent or awareness and to unknown ends. By studying social network judgment accuracy, we have expanded the universe of attributes that can be accurately perceived, which may heighten concerns about what can be learned from the rapidly proliferating digital thin-slice content across various platforms.

Practically, we provided researchers with the standardized and free Social Network Accuracy Test (SNAT), with preliminary validity data. This test contributes to a small but growing body of standardized interpersonal accuracy assessment tests, many of which are outdated (i.e., 20-plus years old), including the Japanese and Caucasian Facial Expression of Emotion Test (JACFEE; Biehl et al., 1997), the DANVA (Nowicki & Duke, 1994) and the Profile of Nonverbal Sensitivity (PONS; Rosenthal et al., 1979); however, there is a newer and freely available test of lie-detection accuracy by ten Brinke et al. (2014). Critically, the SNAT is the first accuracy test to contain information about social network characteristics; we hope it will be a useful contribution to researchers who can use the videos and raw social network data to ask new and important questions beyond what is reported here. The measure fills a gap in research on this topic, particularly given how critical social networks are to professional attainment in organizations and careers more broadly (Burt, 1992; Kilduff & Krackhardt, 2008).

7.3. Limitations and directions for future research

These studies have many limitations; however, each is an opportunity for future research. First, while self-reported egocentric network data is the gold standard in social network survey research, it primarily elicits strong ties rather than weak acquaintances within one's social network. To study network breadth in an acquaintance network, for example, researchers may benefit from using alternative name generators that elicit weaker ties (Burt, 1984). Future research could investigate if perceivers can detect the global composition of a person's network, which would benefit from measuring a target's weaker network contacts. Network survey methods are also susceptible to various forms of reporting bias (Marsden, 2011). Future studies should draw on alternative measures of targets' networks, such as those derived from email archives, email traffic within an organization, or other communication platforms to determine the number and strength of contacts, their composition (e.g., gender, race, family), and their interconnectedness (Alt et al., 2021; Kleinbaum et al., 2013; Srivastava et al., 2018).

Second, we conducted three of the four studies in a laboratory context. While the laboratory approach allows for the creation and testing of controlled stimulus materials that eliminates potential alternative explanations, it is unclear how the capacity to read others' social networks might vary based on the social context in which evaluations are made or on the social standing of those being evaluated. We made preliminary headway on this question in Study 3, which generalized our results to judging a stranger after a face-to-face negotiation. However, further fieldwork is needed to identify the contextual moderators and consequences of interpersonal network judgments across contexts in additional naturalistic settings. Additionally, Study 3 was conducted over Zoom during the time of Covid-19; studying in-person interactions would be an obvious next step once such research is possible again. In a related vein, extant research has demonstrated that digital records from social media platforms such as Facebook can be used to accurately predict a range of personal attributes, such as sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age, and gender (Kosinski et al., 2013; Matz et al., 2017). Future research could explore whether digital video content—akin to TikTok, YouTube, Instagram, Snapchat, and Facebook videos—could be used to accurately detect social network attributes.

Third, future research may also benefit from studying other measures of network composition provided by the SNAT. For example, in university settings, which type of homophily—racial, gender, or race and gender—dominates perceivers' judgments? Do students tend to overestimate the degree of interconnectedness in underrepresented minorities' networks? Research examining both the accuracy and errors in how people perceive others' social worlds can yield rich insights underlying social structures constructed in adult life.[14] It is worth noting that the percentage of white or Asian American people at the university where Studies 1, 2a and 2b were conducted is very high, to the exclusion of other social groups (e.g., Black and/or African American, Latinx). So, while it is possible to calculate (from the raw network data provided) the racial diversity in the SNAT targets' networks, diversity is low, given the fairly homogeneous population from which these SNAT targets come; however, whether racial or ethnic diversity of a stranger's social network can accurately be detected remains an empirical question. Likewise, further work is needed to examine whether people with the capacity to accurately detect social network characteristics are able to avoid costly errors and make better choices about which social relationships to form, activate, or let decay. The thin-slice toolkit and the standardized, validated, and free SNAT provide a means of more systematically measuring and comparing this capacity across individuals and groups.

Fourth, our results point to a previously unexamined source of variation in people's ability to accurately read strangers' social network characteristics that could lead to a potential advantage in navigating and exerting agency within one's social structure (Emirbayer & Goodwin, 1994; Fligstein & McAdam, 2012; Gulati & Srivastava, 2014). Using the SNAT, future research could study what people gain or lose from social network accuracy about strangers, at work and beyond. Additionally, it would be interesting to learn whether people aware of their ability to accurately judge others' social networks. If so, does this awareness help them select better people when dating, hiring, or asking for various forms of support?

Lastly, our findings extend knowledge about how people encode, represent, retrieve, and perceive complex social network information, which is fundamentally different from non-social information (Janicik & Larrick, 2005). Future research can explore which qualities of cognition facilitate accuracy through the perception of these social behaviors.[15] For example, women, positive moods, and low-power manipulations tend to be associated with more accurate judgments about hypothetical novel social networks (Brashears et al., 2016; Hlebec & Ferligoj, 2001; Simpson & Borch, 2005; Simpson et al., 2011). Further research is needed to study whether these qualities also moderate *accurate* judgments about the social networks of unknown others.

8. Conclusion

Judgments about a stranger's social network are ubiquitous in daily life. For example, early-stage entrepreneurs often want to meet people whose networks they assume include connections to angel investors and venture capital firms (Huang & Knight, 2017). Similarly, professionals monitor information about potential exchange partners and the networks of relationships around them to get along and get ahead (Dunbar, 2008; Flynn et al., 2006), and attend networking events to connect with those they believe are embedded in particular organizations and industries (Casciaro et al., 2014). Also, health policymakers and school administrators look for people central in their community networks to target when developing responses to systemic problems (Banerjee et al., 2014) and trying to influence other students' behavior (Paluck et al., 2015), respectively. These examples share a common denominator—making judgments about a person's social network characteristics based on limited information.

Our results indicate that, to an extent, people make accurate judgments about strangers' social network characteristics. Across our four lab and field studies with different samples, we established that after brief exposure to a thin slice of a stranger's recorded behavioral stream or a live interaction with them, perceivers accurately assessed the stranger's social network using the thin-slice paradigm; perceived social-behavioral tendencies facilitated (or hindered) this judgmental accuracy (or lack thereof) in theoretically consistent ways. Finally, we hope that the freely available SNAT proves to be a useful tool for the research community.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors wish to thank Emily Reit, Pooja Gupta, Nathan Simani, Lauren Harris, Isabel Corser, Divya Govindarajan, Merusha Mukherjee, Charlotte Puscasiu, Jeremy Levine, and Vera Palczynski for research assistance and Sameer B. Srivastava, Mathijs de Vaan, Andreea Gorbatai, Ming Leung, Jo-Ellen Pozner, Juliana Schroeder, and members of the Micro Lab and the Berkeley-Stanford Doctoral Conference for valuable feedback on prior drafts. This research was supported by funding from UC Berkeley's Xlab and Behavioral Laboratory.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.obhdp.2021.09.002.

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[14] See the Supplemental Materials for data and discussion of the kinds of accuracy errors that perceivers made in Study 1.

[15] See the Supplemental Materials for a richer discussion about the relationship between lay beliefs about networking and accuracy.

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