Assessing the Accuracy of Interpersonal Judgments about Social Networks

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Abstract

In brief online or face-to-face interactions, people constantly make judgments about others’ social networks. These inferences matter in contexts as diverse as hiring, venture capital funding, advice seeking, policy targeting, and courtship encounters. Yet it remains unclear whether people are accurate in assessing the social networks of strangers and, if so, which behavioral cues perceivers use to form these impressions. Drawing on the “thin-slicing” paradigm in social psychology, which directly tests the accuracy of such routine and rapid judgments, and using data on over 4,276 judgments made by 586 perceivers about 23 strangers, we find that people can accurately infer the size and composition of others’ networks. They are not, however, accurate in assessing the density of another’s social environment.
INTRODUCTION

Based on brief encounters with unfamiliar individuals or fleeting glimpses of strangers, people quickly form initial, often lasting impressions about others’ personal characteristics and social positions (e.g., Ambady and Rosenthal 1992). These inferences are routine and can have material consequences in decisions as wide-ranging as choosing whom to hire (e.g., Rivera 2012), which new venture to fund (e.g., Shane and Cable 2002), which individuals to target in a new policy intervention (Banerjee et al. 2016), and whom to date (e.g., McFarland, Jurafsky, and Rawlings 2014). These interpersonal judgments are made through two distinct but complementary cognitive processes: “top-down,” based on social categorical information such as gender and race; and “bottom-up,” based on observations of enacted behavior (e.g., Bar et al. 2006).

Social networks represent one important component of these interpersonal evaluations. Judgments about the size, composition, and quality of others’ social networks can influence judgments of their potential worth. For example, a hiring manager’s assessment of an applicant for a sales position may be shaped by impressions of her pre-existing ties to prospective clients in a target industry sector. A venture capitalist’s evaluation of an entrepreneurial team may hinge on implicit assumptions about their ability to operate as a structural bridge between the scientific and commercial realms. And appraisals of the attractiveness of a potential dating partner may depend in part on intuitions about the importance of family ties in her social life. As people have access to fleeting glimpses of an increasing number of strangers—for example, through online images, brief videos, and social media platforms—investigating the accuracy of rapid judgments made about others’ social networks is increasingly important.

Prior work has demonstrated the many ways in which interpersonal judgments about social networks can be inaccurate and biased by factors such as sex, personality, affect, status, and power (Casciaro 1998; Simpson and Borch 2005; Kilduff and Krackhardt 2008; Brashears, Hoagland, and Quintane 2016). Yet these studies have focused on the accuracy of cognition about aggregate network structure among a set of known contacts (Simpson, Markovsky, and Steketee 2011; Brashears 2013; for a review, see Kilduff and Krackhardt [2008]). To our knowledge, no prior study has examined the correctness or fallibility of interpersonal judgments about the social networks of individuals who are
unknown to the perceiver. Thus, it remains unclear whether people can accurately assess the size, composition, and shape of the networks of unfamiliar others when making judgments such as whom to hire, whom to date, whom to ask for advice, whose new venture to fund, or whom to target for a new policy intervention.

To make initial progress on this agenda, we investigate three core questions: (1) How accurate are the inferences people draw about the social networks of unknown others as compared to the accuracy of other types of interpersonal judgments? (2) Insofar as people are accurate in these judgments, to what extent are accurate judgments driven by behavioral (e.g., nonverbal) cues expressed above and beyond observable social category information such as gender or age? (3) To the extent that people rely on behavioral expressions such as smiles, gestures, and vocal pitch, which specific ones lead them to make accurate or inaccurate inferences?

To address these questions, we draw upon the “thin-slice” paradigm from social psychology, which involves capturing brief moments of expressive behavior from a longer stream of behavior and uses these “thin slices” of behavior as prompts to study the accuracy of interpersonal judgments made by a separate group of perceivers. The thin slicing paradigm has not only demonstrated the prevalence of rapid, instantaneous evaluative judgments but also shown that these evaluations are predictive of consequential outcomes such as subsequent assessments of teaching effectiveness or job performance (Hecht and LaFrance 1995; Ambady and Rosenthal 1993). Extending this paradigm to the realm of social networks, we compiled a data set that includes 2,166 interpersonal judgments made by 375 perceivers of the social networks of 23 targets. We also ran a second replication study, which validated the results of the main study, using a sample of 2,110 judgments made by 211 perceivers using 10 targets from the original study.

TOP-DOWN AND BOTTOM-UP MODES OF INTERPERSONAL JUDGMENT

The impressions one forms of unknown others are the joint outcome of two distinct modes of social perception: top-down and bottom-up (Biederman, Glass, and Stacy Jr. 1973; Grossberg 1980;
Gilbert 1999; Bar et al. 2006). Both modes are operative when one interacts with, or even thinks about interacting with, others and are driven by the conscious and unconscious noticing, processing, and interpreting of social and behavioral cues (Hall, Bernieri, and Carney 2005).

In top-down interpersonal judgment, people draw inferences about others based on the social categories—for example, gender, race, or age—to which others belong and the stereotypes and assumptions commonly associated with these categories (Asch 1946; Fiske, Lin, and Neuberg 1999; Gilbert 1999). Cues based on certain types of social category membership have also been conceptualized as diffuse status characteristics (e.g., gender), which are associated with general expectations about a person’s anticipated performance in a range of social situations (Berger, Cohen, and Zeldich 1972; Correll 2004; Ridgeway 2014). Top-down processing relies on one’s holistic view of social categories such as “women” or “men.” Research in this tradition has demonstrated, for example, that assessments of others’ competence can be powerfully shaped by perceptions of the gender identity they enact (Ridgeway and Correll 2004).

Top-down approaches facilitate fast judgments and afford cognitive efficiency but are also susceptible to various forms of bias that can lead to inaccurate perceptions (McCauley 1995). For example, people are more likely to pay attention to evidence that confirms their expectations and have trouble incorporating individuating information about others (Trope and Thomson 1997). Similarly, evidence abounds that employers draw on stereotypes—for example, about black men and women, working mothers, and gay men—when deciding whom to hire (Moss and Tilly 2001; Ridgeway and Correll 2004; Tilesik 2011). Stereotypes even pervade financial markets—for example, credit examiners draw on gender stereotypes to make judgments, which often prove inaccurate, about the creditworthiness of female- versus male-led firms when economic conditions are difficult (Thébaud and Sharkey 2016).

In contrast to top-down judgment that privileges information based on social category membership, bottom-up assessments rely on observable behavior regardless of whether or not it is

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2 These two modes have also been characterized as “gestalt,” “system 1,” or “automatic,” and “elemental,” “system 2,” or “controlled” approaches to social information processing (Asch 1946; Fiske, Lin, and Neuberg 1999; Kahneman 2003; Casciaro 2017)
stereotype-consistent. Bottom-up cognitive processing relies on the fact that people routinely reveal—sometimes on purpose and other times without awareness or control—information about themselves through automatically expressed gestures, speech patterns, physical mannerisms, and other forms of expressive behavior. Specifically, bottom-up processing focuses on the impressions people form of others when they interpret observable cues and then combine those signals to form an overarching assessment. Judgments based on bottom-up processing also rely on additional observable cues that people “give off” in expressive behavior, through their clothing and other ornaments, and by virtue of their physiognomic attributes such as facial structure (e.g., Goffman 1959). When people make judgments about others, they automatically engage both modes of cognitive processing, which sometimes leads to accuracy in social judgment and other times to error.

THIN SLICES OF SOCIAL BEHAVIOR

Within social psychology, a robust paradigm—thin slicing—has emerged to examine whether and how people can accurately decode the personal characteristics of strangers. This paradigm relies on perceivers’ judgments of unfamiliar others based on momentary observations of audio clips, photographs, or video clips, which reveal both social categories and speech patterns and nonverbal mannerisms (Ambady and Rosenthal 1992; DePaulo 1992; Feinberg, Willer, and Keltner 2012; Rogers, ten Brinke and Carney 2016). Evolutionary and social psychologists have argued that accurately assessing others’ characteristics based on brief social encounters can often have functional value. For example, fast and automatic judgments about dominance, social status, and social position can help people gather information about who has resources that can help them survive (Willis and Todorov 2006; Oosterhof and Todorov 2008). In the modern world, people regularly observe and draw inferences from thin slices of others’ behavior that they see on the various digital and social media platforms they participate in.

We also draw on a descriptive tool from social and personality psychology, the Brunswikian lens model, to investigate the ways through which people draw accurate inferences about others (Brunswik 1952, 1956). This approach asserts that meaningful differences in traits can be reliably
judged by strangers because tendencies to use expressive cues are associated with underlying traits. Some cues, such as facial expressions of authentic happiness, are universal, hard-wired, and shared by all human species (Ekman 1992). At the same time, a great deal of cultural variation surrounds the expression of nonverbal cues. For example, making eye contact with a colleague at work evokes a sense of connection in Western cultures but may signal disrespect or challenges to dominance in some East Asian cultures (Hawrysh and Zaichkowsky 1990; Akechi et al. 2013).

Not only are such judgments about unfamiliar others quick, automatic, and effortless, they are often remarkably accurate—including assessments of others’ feelings of happiness, sadness, anger, or fear (Ekman 1993); personality traits such as agreeableness, conscientiousness, and extraversion (Kenny 1991; Ickes 1993; Borkenau and Leibler 1993, 1995; Gifford 1994; Funder 1995; Carney, Colvin, and Hall 2007); intention to vote in an upcoming election (Rogers, ten Brinke, and Carney, 2016); and sexual orientation (Rule et al. 2008; Rule, Ambady, and Hallett 2009). Although this literature has produced strong evidence that people make accurate judgments about others based on brief observations, it has stopped short of examining whether a person’s ability to make accurate inferences extends not only to others’ personal, but also to their social, characteristics such as the network in which they are embedded.

RAPID JUDGMENTS ABOUT SOCIAL NETWORKS

We propose that, when encountering strangers, people will seek to make assessments about three core layers of their social networks. These layers correspond to widely studied social network characteristics—size, composition, and density—and represent varying depths of social structure. The first layer, which we anticipate will be easiest to draw accurate inferences about, is simply the number of individuals to whom the target is connected. All else equal, the more network connections a person has, the more likely she is to be a conduit to a greater amount and variety of social resources (Marsden 1987; Wellman and Wortley 1990). For example, when starting at a new school, a new

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3 Another complementary approach in social psychology is referred to as the social-functional approach. It argues that cues (e.g., vocal tones, facial expressions, and arm movements) can reveal how people aim to influence others. Relative to the Brunswikian lens model, it places greater emphasis on the various strategic functions that cues serve to fulfill (Ekman and Friesen 1969; Keltner and Kring 1998).
student might scan peers in the lunch room, with an eye to assessing who is popular and could be a source of introductions to new friends.

The second layer people seek to assess when evaluating strangers, the composition of their network ties, can provide further clues about the nature of resources they could potentially unlock but, we expect, will be harder to ascertain correctly than simply the size of another’s network (Lin, Ensel, and Vaughn 1981). Those with greater network range (Burt 1983) in the form of a lower proportion of same-gender ties, may afford access to a more diverse social world. For example, a female employee joining a male-dominated workplace and searching for new mentors might draw rapid inferences about which female managers are likely to be connected to male executives. Similarly, in the more personal realm of dating, people may draw inferences about the kinship ties of strangers they encounter when making judgments about who might be compatible with their own preferences for maintaining family relations.

The third layer people try to assess, network density, can provide even richer information about the nature and quality of social resources that a stranger possesses; however, we expect it will be the most difficult layer to penetrate based only on thin-slice observations because it requires knowledge about the nature of connections among a person’s contacts. Network density references the extent to which people in the local social environment surrounding a person are connected to each other. Dense networks can support group stability through the enforcement of norms (Coleman 1986). At the same time, sparse networks can facilitate the exchange of non-redundant information, which in turn fuels creativity and innovation (Burt 1992). For example, when evaluating which entrepreneurs to fund, a venture capitalist may implicitly seek to assess the extent to which they are brokers who connect otherwise disconnected social group and, by virtue of this structural position, have access to non-redundant information and ideas that will enable them to innovate (Burt 2004). We turn next to assessing the accuracy of interpersonal judgments about network size, composition, and density.
METHOD

Data Collection—Overview

There were two main components of our data collection effort. First, we produced thin-slice video content for, and assessed the personal and social network characteristics of, 23 target individuals. Then, at a later time, we recruited a second set of perceivers to view the videos for a subset of targets, assess targets’ social network characteristics, and provide information about their own personal and network characteristics. We selected perceivers who had no preexisting relationship to the targets to ensure that interpersonal judgments were based on social cues “given off” by targets in their video presentations rather than on personal or reputational knowledge that perceivers might have had about targets (Goffman 1959; Funder and Colvin 1988). Splitting our data collection in this manner was critical for assessing whether people have the ability to draw accurate inferences about others’ social networks in the absence of other contextual cues or direct interaction with them.

Data Collection—Targets

We recruited 23 participants (57% female; average age of 25, ranging from 19 to 38) into an experimental laboratory at a west coast university to serve as targets for the study. To reduce variation in accuracy stemming from possible differences in perceivers’ ability to read social cues across racial groups, we recruited only white participants as targets. Targets were paid $15 for a one-hour study.

Targets began by completing an ego-centric network survey. Although people may not accurately recall whom they interact with on a given day (see Bernard et al. [1984] for a review), Freeman, Romney, and Freeman (1987) show that people are capable of recounting enduring patterns of relations. Thus, responses to an ego-centric network survey can be taken as a valid proxy for a target’s actual network.

We used a standard name-generator question (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.4 They then indicated the gender of each person they named and their relationship to the person (i.e.,

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4 Of the 23 targets in our study, only four reached the limit of eight when naming their contacts.
spouse, other family member, friend, professional contact, or other). Finally, we asked targets to identify which of their contacts had close or very close relationships with one another. We used this matrix of interrelationships to calculate each target’s network constraint (described in greater detail below).

Next, targets generated thin-slice content about themselves using a video recording tool that was embedded in the survey. We presented targets with five questions designed to get them to speak and act in an authentic, natural, and casual manner. In thinking about this design, we focused on capturing elements of targets’ expressive behavior that are dependent on enduring qualities of a person, rather than on ephemeral or contextual factors. Because social judgments are primarily enabled through informal interactions, we sought to create for each target a context of “sociability” that was explicitly dissociated from economic, business, or instrumental pursuits (Simmel and Hughes 1949; Weber 1994).

Following standard practice in the thin-slicing literature, we used videos rather than still frames because the former are more likely to contain information that people use to encode observations of others (Ambady, Bernieri, and Richeson 2000). Targets were filmed using laptop webcams, which allowed them to control when filming started and stopped. Filming served to orient participants to the presence of real or imagined person, subtly motivating participants to enact behaviors consistent with how they would behave in an introductory interaction—a performance from which others might form first impressions of the individual. A virtue of this approach is that it simulates a social interaction with another person while holding constant potentially confounding factors such as variation in the social environment in which the person is observed or variation in how that individual responds to a particular discussion partner.

Also in line with the typical approach used in thin-slicing research, we chose five broad, open-ended questions designed to prompt targets to express themselves freely. We asked targets to make video recordings of themselves responding to these questions: (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 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?”

Targets produced videos ranging in length from one to two minutes. Also in line with
standard practice in the thin-slicing literature, we took the first twenty seconds of a target’s response
to each question and combined these segments to create a brief montage for each target (Ambady et
al. 2000; Carney et al. 2007). Table 1 provides the responses to thin-slice generating questions from
three representative targets.

*** Table 1 about here ***

To rule out the possibility that perceivers’ judgments about targets’ networks were based on
personal characteristics that are merely correlated with social network characteristics—for example,
to account for the possibility that extraverts actually have more contacts and also seem to others like
they have more contacts—we also asked targets to complete the Big Five Inventory: 44 items that
measure the five core personality traits of extraversion, agreeableness, openness, conscientiousness,
concluded by providing demographic information such as their age, nationality, sex, race, marital
status, and sexual orientation.

Data Collection—Perceivers

We recruited 381 participants (63% female; mean age of 22) at a west coast university into an
experimental laboratory to serve as perceivers for the study. Although all targets were white, we were
unable to fully standardize the race of target-perceiver pairs since it was not possible to recruit only
white perceivers. The racial mix of perceivers was: 58% Asian, 35% White, 10% Hispanic, and 2%
Black. (Note that the sum is greater than 100 because perceivers were able to select multiple racial
categories). In supplemental analyses (not reported), we estimated models that included perceiver race
as a control and that yielded comparable results to the ones reported below.

Each perceiver spent about an hour making various judgments about targets based on their
brief video clips. Six participants did not finish the session and were therefore excluded from the final
analysis, resulting in a final sample size of 375 perceivers, who were each paid $15. Given time
constraints and following Carney et al. (2007), we asked each perceiver to view and make judgments about the videos of a subset of targets (5.8 targets on average). We randomized the order in which targets’ videos were presented for each perceiver.

Our key variables of interest were based on perceivers’ perceptions of targets’ social networks. To reduce the cognitive burden on perceivers, we used visual network scales wherever possible (Mehra et al. 2014). For example, rather than having perceivers estimate the percentage of a target’s contacts that are female, we hired a graphic designer to draw stylized images of networks that vary in gender composition. Figure 1 provides an example of this visual network scale. Although the visual scale provided anchors in the form of the network pictures depicted in Figure 1, perceivers used a slider scale to indicate the proportion of female contacts in a given target’s network. Thus, perceivers’ assessments were based on a continuous measure and compatible with the measure used in targets’ self-reports.

*** Figure 1 about here ***

Figure 2 shows the visual network scale we provided perceivers to assess network constraint in targets’ networks. Perceivers were asked to indicate which of the network diagrams best approximated the degree of interconnectedness in a given target’s network. We calculated the network constraint measure corresponding to each point in the visual scale, assuming no difference in the intensity of ties depicted.

*** Figure 2 about here ***

Perceivers made two kinds of judgments about targets: (1) their proximate social structure, as reflected in the size and gender and kinship composition of their reported network; and (2) their distal social structure, as indicated by the extent to which their reported contacts were themselves connected to each other. After making these assessments, perceivers completed an ego-centric network survey and the Big Five Inventory for themselves and provided information about their own demographic background. These data enabled us to examine whether the accuracy of perceivers’ perceptions was a function of their own personal or social characteristics.
Dependent Variables

Our main dependent variable focuses on the accuracy of perceivers’ judgments about the network characteristics of targets whose videos they were assigned to view and evaluate. Using “profile correlations,” a procedure widely used in thin-slicing research, we calculated accuracy scores across the four social network characteristics—size, gender composition, kinship composition, and constraint—that each perceiver assessed across all targets assigned to that perceiver (Carney et al. 2007; Hall et al. 2005). Network size was based on a straight count of reported contacts. Network composition was based on the proportion of male versus female contacts reported and the proportion of kinship ties versus non-kinship ties reported. For constraint, we used Burt’s (1992) standard measure:

\[ C_i = \sum_j c_{ij}, \ i \neq j \]  

where \( C_i \) is network constraint on target \( i \), and \( c_{ij} \) is a measure of \( i \)’s dependence on contact \( j \).

\[ c_{ij} = \left( p_{ij} + \sum_q p_{iq} p_{qj} \right)^2, \ i \neq q \neq j \]

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 \( j \).

In line with prior work (Ambady et al. 2000; Funder 1987), we operationalized accuracy as the correlation between each perceiver’s judgment about a particular network characteristic across various targets and those targets’ actual self-reports about the same characteristic. We calculated the Pearson’s correlation coefficient between perceivers’ judgments and targets’ self-reports, taking into account that each perceiver judged multiple targets. This resulted in a vector of correlations for each social network characteristic that contained one accuracy score for each perceiver.

Following the thin-slices paradigm, an accuracy score not significantly different from zero indicates no correlation, or no systematic variation, between perceivers’ judgments and targets’ self-reports about a particular network characteristic. It suggests that perceivers are not accurate in drawing inferences about that feature of the target’s network. By contrast, a score significantly greater than zero indicates a positive relationship between perceivers’ judgments and targets’ self-reports. In other words, an accuracy score significantly greater than zero suggests positive alignment between
perceivers’ judgments of a target’s network characteristic and the target’s self-report of the same characteristic (which we assume to approximate the truth).

It is possible to obtain a negative profile correlation, which, suggests that a judgment is inversely related to an actual target’s characteristics. A negative correlation can occur when a naïve perceiver has an inaccurate implicit theory about a particular behavioral tendency, for example, such as thinking that liars “look away” from the person to whom they are lying (Hartwig and Bond 2011). In fact, liars do not look away: they are just as likely to make excessive eye contact, and the net effect is no significant correlation between eye gaze and whether or not a person is lying. When perceivers hold the prevailing stereotype that liars avoid eye contact when lying, their accuracy scores about when targets are lying or telling the truth are typically negative or statistically indistinguishable from zero.

Control Variables

A growing body of evidence documents the ways in which personal characteristics such as gender, age, and personality traits are related to social network characteristics (e.g., Burt, Kilduff, and Tasselli 2013). To account for the possibility that perceivers were merely making accurate interpersonal judgments about targets’ personal characteristics (e.g., gender, age, and extraversion), which just happened to be correlated with social network characteristics (e.g., network size), we included targets’ gender, age, and perceived Big Five personality traits as control variables in supplemental analyses described below. We also conducted supplemental analyses in which we controlled for targets’ actual Big Five personality traits and the personal and social network characteristics of the perceivers themselves. Our results were substantially unchanged when we included either set of control variables. We report the former set of results below. The latter are available upon request but not reported for the sake of brevity.

Assessing Accuracy

To assess the accuracy of perceivers’ judgments about targets’ social network characteristics, we conducted one-sample t-tests to assess whether the mean of perceivers’ accuracy scores for different social network characteristics was greater than zero. As noted above, the null is that perceivers’ accuracy is no different from zero, meaning that there is no relationship between
interpersonal judgments and targets’ actual social networks. Although our hypothesis about accuracy is directional (i.e., greater than zero), we conservatively report two-tailed tests. Figure 3 provides a visual representation of this analytical approach.

*** Figure 3 about here ***

To evaluate the accuracy of perceivers’ judgments of targets’ network characteristics net of targets’ personal characteristics, we conducted supplemental ordinary least squares regressions of accuracy in which we controlled for targets’ gender, age, and perceived Big Five personality traits and, separately, for perceivers’ Big Five personality and social network characteristics. Because perceivers made multiple judgments across targets, we clustered standard errors in these models by perceiver.

**Behavioral Cues Associated with Social Network Characteristics**

We conducted supplemental exploratory analyses to determine the behavioral cues perceivers used in assessing targets’ network characteristics. Following commonly used methods in the study of behavioral cues, two research assistants, who were blind to our research questions and study design, coded targets’ video content. In particular, we focused on behavioral cues related to perceived sociability and status because they encompass both expressive and instrumental forms of social interactions (Lin 2001). Behavioral expressions of sociability include smiling, gesturing, making eye contact or maintaining eye gaze, head nodding, talking more, and referencing others more in conversation (Gifford 1994; Lippa 1998; Pennebaker, Mehl, and Niederhoffer 2003; Scherer 2003).

The inverse of sociability, social anxiety, can be reflected in behavioral cues such as speaking less, averting eye contact, the absence of gestures or smiles, as well as self-focused behaviors such as touching one’s own neck, head, arm, or hand, pausing, or speaking dysfluently (Muirhead and Goldman 1979; Riggio and Friedman 1986; Harrigan et al 1987; Knapp, Hall, and Horgan 2013). Cues associated with status include tilting one’s head up, speaking loudly, speaking more relative to listening, and the absence of fidgeting (Pennebaker et al. 2003; Tracy and Matsumoto 2008; Gravano et al 2011).

To detect these cues, research assistants coded most of the behaviors observed in targets’ videos through their own direct observation. However, because linguistic and speech-related
behavioral cues are more difficult for coders to observe, we instead used a commonly used software package—Praat—to assess acoustic cues (Boersma and Weenink 2012). After practicing coding on a training set of videos (i.e., videos not used in our study), the two human coders assessed a randomly chosen subset of four videos to establish that inter-rater reliability was above 0.7—the threshold commonly used in such studies. Once inter-rater reliability was established for an expressive behavioral cue, one coder was responsible for coding that particular behavioral cue across all videos.

Table 2 lists all behaviors coded, definitions, associated references to relevant research, coding scales, approach, and associated inter-rater reliability. We report all correlations that exceed $r = 0.2$ because these types of social psychological effects typically yield a value of $r$ equivalent or greater than 0.2 (Richard, Bond Jr., and Stokes-Zoota 2003).

*** Table 2 about here ***

RESULTS

Table 3 reports descriptive statistics for both targets’ actual network characteristics and perceivers’ judgments of those characteristics: network size, proportion of male ties, proportion of kinship ties, and network constraint. The first and second columns report targets’ actual social network characteristics and perceivers’ perceptions of social networks, respectively.

*** Table 3 about here ***

Table 4 reports results of t-tests evaluating whether perceivers’ mean accuracy scores about targets’ social network characteristics were greater than zero. 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 sample size of perceivers’ judgments varied slightly across social network characteristics.

For accuracy about network size of a target, scores ranged from -0.96 to 0.97, with a mean of .09. For accuracy about the gender composition of targets’ networks, measured as proportion of male contacts, values ranged from -0.84 to 1, with a mean of .33. Accuracy about the proportion of kinship ties ranged from -0.94 to 0.97 and the mean was .07. The t-statistics for network size, proportion of kinship ties, and proportion of male ties were all greater than zero and highly significant ($p < .001$),
providing strong and consistent evidence that people can be accurate when making judgments about these social network characteristics of unfamiliar others, based only on thin-slice observations of them.

To put these accuracy scores in context, we compared our findings with accuracy scores about target’s personal characteristics and other published research on accuracy scores of personal, rather than social, characteristics. Perceivers’ judgments about targets’ Big Five personality characteristics and socioeconomic status ranged from -0.06 to 0.23, which is comparable to accuracy scores for their social network characteristics. However, the accuracy scores reported here fall slightly below the range identified in prior research, .04 to .55, when perceivers were asked to make predictions about targets’ personality traits (Ambady et al. 2000; Carney et al. 2007). Because the ability to make accurate judgments about personality characteristics relies, in part, on abundant and readily observable cues (Funder 2001), it is not surprising that accuracy scores based on more directly observable personal characteristics, such as extraversion, tend to be higher than the ones we report for social network characteristics (Funder and Sneed 1993).

The t-test of the accuracy of judgments about network constraint suggests that there are limits to which people can see into others’ social worlds. Accuracy scores for network constraint ranged from -0.99 to 0.93, with a mean of -0.01. The test statistic for network constraint accuracy was -0.42 and not significant. Thus, our results suggest that, although people appear to be able to make accurate judgments about others’ proximate social structure, they are inaccurate when making judgments about the distal social structure—defined by the nature of connections among a target’s reported contacts.

*** Table 4 about here ***

Table 5 reports results of regressions of accuracy scores on targets’ gender, age, and Big Five personality traits. To isolate the role of expressive behaviors in social network judgments, we control for targets’ social category membership (e.g., gender), which perceivers process through top-down judgments. In these models, we mean-centered all five target personality variables such that the intercept represents perceivers’ accuracy scores for a target at the mean of all five personality variables. We report the intercept and corresponding confidence intervals from these models. The results are consistent with those reported in Table 4 and suggest that, even after accounting for
targets’ gender, age, and personality traits, perceivers can make accurate judgments about the size and composition of their networks. They are not, however, able to make accurate judgments about the nature of connections among targets’ reported contacts. In the specification shown in Table 5, perceivers’ accuracy score about targets’ network constraint is negative and significant. That is, perceivers are inaccurate when they assess the degree of constraint in strangers’ networks. While the negative sign of the intercept for accuracy about network constraint is consistent across various model specifications, the significance of the effect varies across specifications.

*** Table 5 about here ***

The Role of Behavioral Cues in Judgments about Social Network Characteristics

Table 6 reports the results of a set of descriptive Brunswikian lens models to illustrate which specific cues proved to be accurately or inaccurately used (or not used at all when they should have been) when perceivers judged targets’ social networks (Brunswik [1952], [1956]; for a recent application, see ten Brinke et al. [2016]). We identify three categories of cues, which provide a window into the lay theories people appear to hold when assessing others’ social networks—(a) cues that are correlated with accurate assessments, (b) cues that are associated with erroneous judgments, and (c) missed cues (i.e., ones that are, in fact, reflective of targets’ actual social network characteristics but tend to be overlooked by perceivers).

*** Table 6 about here ***

Perceivers correctly assessed that the extent to which a target gestured was positively associated with network size. They missed, however, the opportunity to draw inferences based on targets’ self-references (e.g., the use of “I” or “me”), eye gazes, and self-touching of the hand or arm region (a form of fidgeting)—cues that were all associated with targets’ actual network size. Smiling and head nods were not related to accurate judgments about network size, although perceivers incorrectly relied on these cues to form impressions. Perceivers also incorrectly associated higher average vocal pitch with larger social networks.

---

5 As a robustness check to account for concerns about the normality of the distribution of accuracy scores, we transformed all four accuracy score dependent variables into Fisher’s z coefficients and ran the same models. The results of these additional analyses (not reported) are consistent with those reported in Table 4.
When making judgments about the gender composition of targets’ networks—in particular, the proportion of male contacts—perceivers accurately inferred that making fewer references to others, speaking with a lower pitch, and speaking with more dysfluencies were expressive behavioral cues associated with a higher proportion of male contacts. Perceivers incorrectly thought that fewer smiles, fewer gestures, less self-touching of the hand and arm region, longer eye gazes, and fewer self-references would be associated with having a more male-dominated network. These cues were not, however, related to targets’ actual proportion of male contacts. Perceivers failed to realize that more gesturing, more fidgeting with the head and neck, and speaking loudly were associated with having a larger proportion of male contacts.

Perceivers correctly noted that targets who used fewer expressive gestures had a higher proportion of family connections. There were many cues that perceivers incorrectly associated with a high proportion of kinship ties including fewer smiles, shorter eye gazes, more head nods, fewer speech dysfluencies, and more self-references. By contrast, making fewer self-references and less fidgeting and self-touching of the head and hand regions were behavioral cues that perceivers failed to attend to but that were actually related to having more family ties.

We do not report results from a Brunswikian lens model for judgments about network constraint because our study yielded no evidence that people are able to make these judgments accurately. Appendices A, B, and C contain visual representations of Brunswikian lens models for judgments about (a) network size, as well as (b) the proportion of male and (c) family contacts.

To establish the robustness of our main findings about the accuracy of social network judgments, we conducted a smaller-scale replication study based on ten targets whose social network characteristics perceivers in the main study were especially accurate in assessing. These results, which corroborate our main findings, are reported in Appendix D.

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6 Inferences based on lower pitch are, of course, related to the gender of the target. It seems likely that perceivers simply assumed that men, who speak at a lower pitch than women, were more likely to have ties to other men based on the principle of homophily (McPherson, Smith-Lovin, and Cook 2001).
DISCUSSION AND CONCLUSION

The goal of this study has been to investigate the accuracy of interpersonal judgments about the social networks in which others are embedded. We did so by drawing upon the tools of the thin-slice research paradigm in social psychology, which is designed to study such rapid and often lasting judgments that routinely occur in everyday life (Ambady and Rosenthal 1992). Controlling for certain diffuse social categories such as gender that trigger top-down processing, we examined the role of bottom-up social information processing in people’s ability to accurately “see” the social structure in which a stranger is ensconced. We found that the accuracy of these assessments is comparable to the accuracy of evaluations of personality traits such as extraversion and agreeableness. Given prior work documenting the myriad ways in which interpersonal judgments about others based on attributes such as gender, race, or age are often fraught with error (e.g., Pager and Shepherd 2008), it is noteworthy that we detect the ability of naïve perceivers to accurately assess characteristics of strangers’ social networks. At the same time, we identified the limits of what people can assess about strangers’ relational patterns: how their contacts are related to each other.

Supplemental, exploratory analyses identified specific behavioral cues appear to support accurate interpersonal judgments, others that contribute to inaccuracy, and still others that are accurate but overlooked by perceivers. For example, perceivers correctly noted that making fewer references to others, having a lower vocal pitch, and speaking with more speech dysfluencies was associated with a higher proportion of male contacts. Overall, the preliminary evidence from this investigation suggests that people use others’ expressive behaviors as cues to make accurate and systematically biased judgments about social networks based on how different social structural positions are embodied, expressed, and enacted.

Limitations and Directions for Future Research

The study is not without limitations, which also point to avenues for future research. First, we rely on self-reported network data, which are susceptible to various forms of reporting bias (Marsden 2011). It would be useful in future studies to include more objective measures of targets’ networks such as those derived from email archives (Kleinbaum, Stuart, and Tushman 2013; Srivastava 2015; Goldberg et al. 2016; Srivastava et al. 2017). Second, we used laptop webcams to gather videos of
targets. It seems likely that targets’ self-presentation in videos differed from the self-presentation they would have had in more natural social interactions. Further work is needed to understand how the accuracy of judgments about networks varies across these contexts. A third, related limitation is that we only used videos of average length and that also included audio content. It remains unclear just how thin a slice of behavior a perceiver can observe and still make accurate judgments about strangers’ social networks. Similarly, it would be useful to examine the role of audio, rather than video, content in judgment accuracy.

More broadly, we conducted our study in the relatively sterile context of university laboratories. It is therefore unclear how the capacity to read others’ positions in social structure might vary depending on the social context in which evaluations are made or on the social standing of the people being evaluated. In addition, although we conjecture that the accuracy of judgments about others’ social networks can have material consequences in domains such as hiring, venture capital funding, and dating, our study was not designed to identify such a link. Further field work is needed to identify the contextual moderators and consequences of interpersonal network judgments.

**Contributions**

The findings from this study make three main contributions. First, two core assumptions underlying many prominent theories of social interaction—ranging from Bourdieu’s (1984) construct of the habitus to Goffman’s (1959) account of impression management—are that: (1) people, even mere strangers, can draw accurate inferences about others based on their expressive behavioral cues; and (2) people routinely reveal information about their place in social structure through cues such as their bodily operations, ordinary behaviors, and mannerisms. Yet the evidence in support of many of these assumptions has been at best indirect (Cerulo 2010; Lizardo and Strand 2010). To our knowledge, this study provides the first direct test of these assumptions, focusing on the social networks of strangers. Our results indicate that information about a person’s proximate structure—network size and composition—can be accurately conveyed to, and perceived by, others; however, information about a person’s distal structure—the density of relations in their social environment—cannot be accurately perceived by others even if it is “given off” in their self-presentation (Goffman 1959).
A second contribution is to the thin-slice research paradigm itself. Research on social perception in social psychology and social cognition shows that people can make remarkably accurate judgments about a variety of personal characteristics ranging from personality traits to teacher effectiveness to patient satisfaction with physicians (Hall, Roter, and Rand 1981; Ambady and Rosenthal 1993; Carney et al. 2007). The current work implies that we do more than simply assess a person’s individual characteristics such as happiness or wealth. Instead, these data suggest that we can accurately assess others’ social characteristics as manifested in their social network. These judgments matter when a person is deciding whom to befriend, hire, sit next to, invest in, or take on as a graduate student.

Finally, our preliminary investigation of expressive behavioral cues helps us construct a more complete understanding of how communication between strangers is successfully exchanged or fails to be exchanged (Ichheiser 1949). Such inquiries into accuracy and error unearth subtle and socially-reinforced perceptions and stereotypes about others’ social network characteristics (Brands and Kilduff 2013). It remains unclear whether people can be trained to correct errors in social structural assessments of others or to pay attention to cues they commonly overlook.

In sum, this study sheds new light on a pervasive feature of social life—interpersonal judgments about others’ social networks. It joins a burgeoning literature (DiMaggio 1997; Cerulo 2002; Srivastava and Banaji 2011; Brekhus 2015; Zerubavel et al. 2015) that underscores the value of drawing on concepts and methods from cognitive and social psychology to address core questions about modern social life.
REFERENCES


Willis, Janine and Alexander Todorov. 2006. “First Impressions: Making Up Your Mind After 100ms Exposure to a Face. Psychological Science 17: 592-598


### TABLE 1: EXAMPLES OF THIN-SLICE VIDEO TRANSCRIPTS

<table>
<thead>
<tr>
<th>Question 1: How would you describe yourself?</th>
<th>Targets’ Responses:</th>
</tr>
</thead>
<tbody>
<tr>
<td>“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…”</td>
<td>“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.”</td>
</tr>
<tr>
<td>“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…”</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Question 2: Can you describe how you like to cook or prepare eggs for yourself or others?</th>
<th>Targets’ Responses:</th>
</tr>
</thead>
<tbody>
<tr>
<td>“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…”</td>
<td>“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.”</td>
</tr>
<tr>
<td>“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…”</td>
<td></td>
</tr>
</tbody>
</table>
**Question 3:** Do you have any advice about how to best prepare for a job interview?

**Targets’ Responses:**
- “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…”

**Question 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?

**Targets’ Responses:**
- “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…”

**Question 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?

**Targets’ Responses:**
- “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…”
<table>
<thead>
<tr>
<th>Behavioral Cue</th>
<th>Definition</th>
<th>Ref(s)</th>
<th>Scale, Range &amp; Mean</th>
<th>Approach</th>
<th>Inter-Rater Reliability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cues Associated with Sociability</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Smiles</td>
<td>Number of smiles. More smiles associated with greater sociability and affiliation seeking.</td>
<td>Patterson 1983; Lippa 1998</td>
<td>Count, Ranging from 0-16, Mean = 4.4</td>
<td>Human</td>
<td>0.91</td>
</tr>
<tr>
<td>Speech illustrative gestures</td>
<td>Number of speech illustrative gestures. This does not include gestures that explicitly communicate specific meanings such as the hand signal for “O.K.” More gestures associated with greater sociability and affiliation.</td>
<td>Gifford, Ng, and Wilkinson 1985; Gifford 1994</td>
<td>Count, Ranging from 0-7, Mean = 1.9</td>
<td>Human</td>
<td>0.81</td>
</tr>
<tr>
<td>References to others</td>
<td>Number of references to others (e.g. &quot;we,&quot; &quot;us,&quot; or &quot;the group&quot;). Pronoun usage reflects the extent to which one focuses on themselves or their relationships with others. More references to others associated with greater sociability.</td>
<td>Pennebaker, Mehl, and Niederhoffer 2003</td>
<td>Count, Ranging from 3-18, Mean = 8.3</td>
<td>Human</td>
<td>0.70</td>
</tr>
</tbody>
</table>
### Cues Associated with Both Sociability and Status

<table>
<thead>
<tr>
<th>Cues</th>
<th>Description</th>
<th>Source(s)</th>
<th>Measure Type</th>
<th>Praat Software</th>
<th>Not applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean vocal intensity</td>
<td>Vocal intensity conveys confidence, desire to engage and have others listen. Greater vocal intensity is associated with greater sociability and status.</td>
<td>Borkenau and Liebler 1995; Scherer 2003; Mairesse et al. 2007; Gravano et al 2011</td>
<td>Vocal decibel (db), Ranging from 48.1 – 64.9 db, Mean = 59.8 db</td>
<td>Praat software</td>
<td>Not applicable</td>
</tr>
<tr>
<td>Self-touching to the head, neck, hair, or face⁷</td>
<td>A self-soothing behavior that engages the parasympathetic nervous system. A touch is defined as a distinct unit of touch with a start and stop which is then counted as on touch. More self-touching is associated with lower sociability.</td>
<td>Goldberg and Rosenthal 1986; Harrigan et al. 1987; Knapp, Hall, and Horgan 2013</td>
<td>Count, Ranging from 0-7, Mean = 1.3</td>
<td>Human</td>
<td>1.00</td>
</tr>
<tr>
<td>Self-touching to the arm, hand, or wrist⁷</td>
<td>A self-soothing behavior that engages the parasympathetic nervous system. A touch is defined as a distinct unit of touch with a start and stop which is then counted as on touch. More self-touching is associated with lower sociability.</td>
<td>Goldberg and Rosenthal 1986; Harrigan et al. 1987; Knapp, Hall, and Horgan 2013</td>
<td>Count, Ranging from 0-6, Mean = 1.3</td>
<td>Human</td>
<td>1.00</td>
</tr>
<tr>
<td>Speech dysfluencies</td>
<td>Utterances such as “um” or “ah.” More dysfluent speech reflects anxiety or increased cognitive load and is associated with lower status.</td>
<td>Riggio and Friedman 1986</td>
<td>Count, Ranging from 1-25, Mean = 11.7</td>
<td>Human</td>
<td>0.96</td>
</tr>
<tr>
<td>Time spent looking at the camera</td>
<td>Maintaining eye gaze in non-competitive human contexts is associated with affiliation and status. Eye gaze signals attention seeking and willingness to give attention to others.</td>
<td>Muirhead and Goldman 1979; Cherulnick 2001</td>
<td>Seconds, Ranging from 31s to 1m 39s, Mean = 1m 22 s</td>
<td>Human + stopwatch</td>
<td>0.97</td>
</tr>
</tbody>
</table>

### Cues Associated with Status

<table>
<thead>
<tr>
<th>Cues</th>
<th>Description</th>
<th>Source(s)</th>
<th>Measure Type</th>
<th>Praat Software</th>
<th>Not applicable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tilting head upward (vertical movements)</td>
<td>Research on pride and status are highly overlapping in social psychology. Pride is the emotion associated with having status. One nonverbal expression that</td>
<td>Gifford 1994; Tracy and Matsumoto 2008</td>
<td>Count, Ranging from 0-7, Mean = 3.7</td>
<td>Human</td>
<td>0.93</td>
</tr>
</tbody>
</table>

---

⁷ Continuous touch that does not stop is counted as 1 (which is sometimes why researchers also code duration).
<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
<th>References</th>
<th>Calculation</th>
<th>Software</th>
<th>Applicability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocal pitch</td>
<td>The minimum, maximum, and mean vocal vibrations observed. Higher means higher status.</td>
<td>Borkenau and Liebler 1995; Liscombe et al. 2003; Scherer 2003; Feinberg et al. 2005; Gravano et al. 2011</td>
<td>Vocal frequency (Hz), Ranging from 101-231 Hz, Mean = 167 Hz</td>
<td>Praat</td>
<td>Not applicable</td>
</tr>
<tr>
<td>References to the self</td>
<td>Number of references to one’s self (e.g. “I” or “me”). Pronoun usage reflects the extent to which one focuses on themselves or their relationships with others. More self-references is associated with higher status.</td>
<td>Pennebaker, Mehl, and Niederhoffer 2003</td>
<td>Count, Ranging from 8-22, Mean = 14.3</td>
<td>Human</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>Targets’ Self-Reports about Social Network Characteristics</td>
<td>Perceivers’ Judgments about Targets’ Social Network Characteristics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------------------------------------------</td>
<td>---------------------------------------------------------------------</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network Size (# contacts)</td>
<td>5.4</td>
<td>4.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion male ties (%)</td>
<td>42.7</td>
<td>50.2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion kinship ties (%)</td>
<td>45.0</td>
<td>33.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Network constraint</td>
<td>0.23</td>
<td>0.38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>23</td>
<td>2,166</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 4: Accuracy of Perceivers’ Judgments of Targets’ Personal and Social Network Characteristics

<table>
<thead>
<tr>
<th>Target Attribute</th>
<th>Mean</th>
<th>t-test greater than 0 (SE)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network size</td>
<td>.09</td>
<td>3.52*** (.02)</td>
<td>366</td>
</tr>
<tr>
<td>Proportion male ties</td>
<td>.33</td>
<td>18.82*** (.02)</td>
<td>375</td>
</tr>
<tr>
<td>Proportion kinship ties</td>
<td>.07</td>
<td>3.18*** (.02)</td>
<td>375</td>
</tr>
<tr>
<td>Network constraint</td>
<td>-.01</td>
<td>-0.42 (.03)</td>
<td>367</td>
</tr>
<tr>
<td>Extraversion</td>
<td>.13</td>
<td>4.83*** (.03)</td>
<td>374</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>.22</td>
<td>10.04*** (.02)</td>
<td>374</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>.23</td>
<td>9.42*** (.02)</td>
<td>373</td>
</tr>
<tr>
<td>Emotional Stability (Neuroticism)</td>
<td>.19</td>
<td>8.45*** (.02)</td>
<td>369</td>
</tr>
<tr>
<td>Openness</td>
<td>-.04</td>
<td>-1.79 (.02)</td>
<td>373</td>
</tr>
<tr>
<td>SES</td>
<td>-.06</td>
<td>-2.57** (.02)</td>
<td>373</td>
</tr>
</tbody>
</table>

Note: Standard errors in parentheses. We were unable to calculate accuracy scores for perceivers’ whose judgments did not vary across targets. The sample size for accuracy scores therefore varied across personal and social network characteristics.

* p < .05; ** p < .01; *** p < .001; two-tailed tests.
**TABLE 5: PREDICTED ACCURACY OF PERCEIVERS’ JUDGMENTS OF TARGETS’ SOCIAL NETWORK CHARACTERISTICS, CONTROLLING FOR TARGETS’ GENDER, AGE, AND PERCEIVED PERSONALITY CHARACTERISTICS**

<table>
<thead>
<tr>
<th>Predicted Accuracy Conditional On Target Gender, Age, and Personality</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Size</strong></td>
<td>.20*** (.05)</td>
</tr>
<tr>
<td></td>
<td>.12 – .29</td>
</tr>
<tr>
<td><strong>Proportion Male Ties</strong></td>
<td>.41*** (.03)</td>
</tr>
<tr>
<td></td>
<td>.35 – .47</td>
</tr>
<tr>
<td><strong>Proportion Kinship Ties</strong></td>
<td>.27*** (.04)</td>
</tr>
<tr>
<td></td>
<td>.19 – .36</td>
</tr>
<tr>
<td><strong>Network Constraint</strong></td>
<td>-.10** (.04)</td>
</tr>
<tr>
<td></td>
<td>-.17 – .02</td>
</tr>
<tr>
<td><strong>Extraversion</strong></td>
<td>.49*** (.06)</td>
</tr>
<tr>
<td></td>
<td>.37 – .62</td>
</tr>
<tr>
<td><strong>Agreeableness</strong></td>
<td>.31*** (.04)</td>
</tr>
<tr>
<td></td>
<td>.23 – .39</td>
</tr>
<tr>
<td><strong>Conscientiousness</strong></td>
<td>.02 (.05)</td>
</tr>
<tr>
<td></td>
<td>-.09 .12</td>
</tr>
<tr>
<td><strong>Emotional Stability (Neuroticism)</strong></td>
<td>-.09 (.06)</td>
</tr>
<tr>
<td></td>
<td>-.21 .02</td>
</tr>
<tr>
<td><strong>Openness</strong></td>
<td>-.24*** (.04)</td>
</tr>
<tr>
<td></td>
<td>-.31 -.15</td>
</tr>
<tr>
<td><strong>SES</strong></td>
<td>-.20*** (.04)</td>
</tr>
<tr>
<td></td>
<td>-.29 -.11</td>
</tr>
</tbody>
</table>

Note: For predicted accuracy about targets’ specific personality characteristics, the four other personality characteristics are included as controls. Robust standard errors in parentheses clustered by perceiver. * p < .05; ** p < .01; *** p < .001; two-tailed tests.
Table 6: The Role of Behavioral Cues in Social Network Judgments

<table>
<thead>
<tr>
<th></th>
<th>Correct Cues Used to Make Judgments</th>
<th>Incorrect Cues Used to Make Judgments</th>
<th>Missed Cues Not Used to Make Judgments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Size (associated with larger network size)</td>
<td>• Greater use of gestures</td>
<td>• More smiles</td>
<td>• More use of “I” and other self-references</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• More head movements</td>
<td>• Longer eye gaze</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Higher average pitch</td>
<td>• More self-touching and soothing to the arm/hand region</td>
</tr>
<tr>
<td>Proportion Male Contacts (associated with higher prop male)</td>
<td>• Fewer references to others (e.g. “them” or “the group”)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• More speech dysfluencies (e.g. “uhm” or “er”)</td>
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<tr>
<td></td>
<td></td>
<td>• Lower average vocal pitch</td>
<td>• Greater number of gestures</td>
</tr>
<tr>
<td></td>
<td>• Fewer references to others</td>
<td>• Fewer smiles and gestures</td>
<td>• More self-touches to head and neck</td>
</tr>
<tr>
<td></td>
<td>(e.g. “them” or “the group”)</td>
<td>• Fewer self-references</td>
<td>• Higher average vocal intensity</td>
</tr>
<tr>
<td></td>
<td>• More speech dysfluencies (e.g. “uhm” or “er”)</td>
<td>• Longer eye gaze</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Lower average vocal pitch</td>
<td>• Less touching to arms and hands</td>
<td></td>
</tr>
<tr>
<td>Proportion Family Contacts (associated with higher prop family)</td>
<td>• Fewer gestures</td>
<td>• Fewer smiles</td>
<td>• Fewer references to one’s self</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• More references to one’s self</td>
<td>• Fewer self-touches to the hand, arm, head, and neck regions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• More head nods</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Shorter eye gaze</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Fewer speech dysfluencies</td>
<td></td>
</tr>
</tbody>
</table>

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FIGURE 1: VISUAL NETWORK SCALE EXAMPLE, GENDER COMPOSITION

Mostly female contacts — Female and male contacts — Mostly male contacts

FIGURE 2: VISUAL NETWORK SCALE EXAMPLE, NETWORK CONSTRAINT

Which of the network diagrams below best approximates the

DEGREE OF INTERCONNECTEDNESS IN THE SUBJECT'S NETWORK?

Please make your selection by clicking one of the pictures below. Imagine the blue center of each image represents the subject ("S") in the video.

1. None of their contacts is a friend of another friend.
2. A few of their contacts are friends with each other.
3. About half of their contacts are friends with each other.
4. Most of their contacts are friends with each other.
5. All of their friends are friends with each other.
FIGURE 3: VISUAL REPRESENTATION OF ANALYTICAL APPROACH

Accuracy score = correlation of ratings and actual values for each social network characteristic

Perceiver

Targets

Rating for Target 1
Rating for Target 2
Rating for Target 3
Rating for Target 4
Rating for Target 5
Rating for Target 6

Actual value for Target 1
Actual value for Target 2
Actual value for Target 3
Actual value for Target 4
Actual value for Target 5
Actual value for Target 6
APPENDIX A: LENS MODEL JUDGMENTS ABOUT NETWORK SIZE

<table>
<thead>
<tr>
<th>Network Size Perception</th>
<th>Behavioral Cues</th>
<th>Target’s Actual Social Network Size</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SMILES</td>
<td>.44</td>
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<tr>
<td></td>
<td>GESTURES</td>
<td>.38</td>
</tr>
<tr>
<td></td>
<td>OTHER-REFs</td>
<td>.10</td>
</tr>
<tr>
<td></td>
<td>INTENSITY</td>
<td>.12</td>
</tr>
<tr>
<td></td>
<td>SELF-TOUCH HEAD</td>
<td>.16</td>
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<tr>
<td></td>
<td>SELF-TOUCH ARM</td>
<td>-.04</td>
</tr>
<tr>
<td></td>
<td>EYE GAZE</td>
<td>&lt; -.01</td>
</tr>
<tr>
<td></td>
<td>HEAD NOD</td>
<td>.25</td>
</tr>
<tr>
<td></td>
<td>SPEECH DYS</td>
<td>.12</td>
</tr>
<tr>
<td></td>
<td>PITCH</td>
<td>.27</td>
</tr>
<tr>
<td></td>
<td>SELF-REFs</td>
<td>&lt; -.01</td>
</tr>
</tbody>
</table>

KEY: Behavioral Cues
- Blue = Sociability cues
- Green = Sociability and status cues
- Red = Status cues

KEY: Line Types
- Thick black = correct cues used to form perceptions
- Thin black dashed = incorrect cues used for inaccurate judgments
- Thin black solid = missed cue, could be used for accurate judgments
APPENDIX B: LENS MODEL JUDGMENTS ABOUT PROPORTION OF MALE CONTACTS

Proportion Male Contacts Perception

Behavioral Cues

- **SMILES**
  - Target’s Actual Proportion Male Contacts: -.07
  - Proportion Male Contacts: -.25

- **GESTURES**
  - Target’s Actual Proportion Male Contacts: .27
  - Proportion Male Contacts: -.24

- **OTHER-REFs**
  - Target’s Actual Proportion Male Contacts: -.20
  - Proportion Male Contacts: -.32

- **INTENSITY**
  - Target’s Actual Proportion Male Contacts: .24
  - Proportion Male Contacts: .17

- **SELF-TOUCH HEAD**
  - Target’s Actual Proportion Male Contacts: .26
  - Proportion Male Contacts: < .01

- **SELF-TOUCH ARM**
  - Target’s Actual Proportion Male Contacts: .13
  - Proportion Male Contacts: -.41

- **EYE GAZE**
  - Target’s Actual Proportion Male Contacts: -.03
  - Proportion Male Contacts: .27

- **HEAD NOD**
  - Target’s Actual Proportion Male Contacts: -.23
  - Proportion Male Contacts: -.16

- **SPEECH DYS**
  - Target’s Actual Proportion Male Contacts: .33
  - Proportion Male Contacts: .31

- **PITCH**
  - Target’s Actual Proportion Male Contacts: -.49
  - Proportion Male Contacts: -.88

- **SELF-REFs**
  - Target’s Actual Proportion Male Contacts: .03
  - Proportion Male Contacts: -.32

**KEY: Behavioral Cues**

- **Blue** = Sociability cues
- **Green** = Sociability and status cues
- **Red** = Status cues

**KEY: Line Types**

- **Thick black** = correct cues used to form perceptions
- **Thin black dashed** = incorrect cues used for inaccurate judgments
- **Thin black solid** = missed cue, could be used for accurate judgments
APPENDIX C: LENS MODEL JUDGMENTS ABOUT PROPORTION OF FAMILY CONTACTS

Proportion Family Contacts Perceiption

Behavioral Cues

- SMILES
- GESTURES
- OTHER-REFs
- INTENSITY
- SELF-TOUCH HEAD
- SELF-TOUCH ARM
- EYE GAZE
- HEAD NOD
- SPEECH DYS
- PITCH
- SELF-REFs

KEY: Behavioral Cues
- Blue = Sociability cues
- Green = Sociability and status cues
- Red = Status cues

KEY: Line Types
- Thick black = correct cues used to form perceptions
- Thin black dashed = incorrect cues used for inaccurate judgments
- Thin black solid = missed cue, could be used for accurate judgments

Target's Actual Proportion Family Contacts
APPENDIX D: REPLICATION STUDY

For the replication study, we collected judgments from 211 perceivers in an undergraduate business class. Each perceiver observed thin-slice videos for ten targets and made judgments about four characteristics of each target’s social network. Our replication study produced substantively similar results to the main study. The mean accuracy score for network size was .11, ranging from -.65 to .75. For accuracy about proportion male, scores ranged from -.78 to .87, with a mean of .45. Accuracy scores for proportion kinship ties ranged from -.48 to .82, with a mean of .19. Lastly, accuracy scores for network constraint ranged from -.78 to .79, with a mean of .01. T-statistics to evaluate whether these accuracy scores were statistically greater than zero were all significant (p < .001), except for network constraint.8

8 To foster further research on this topic, we will, upon publication of this paper, make publicly available our social network thin-slicing assessment tool, including full network, demographic, and personality information for the targets.