**Differential Associations of Knowing and Liking with Accuracy and Positivity
Bias in Person Perception**

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Abstract

A great range of person perception phenomena may be conceptualized in terms of how much perceivers know about the targets, how much they like the targets and how these factors relate to the extent to which target descriptions reflect actual target characteristics and/or evaluative bias. We present a comprehensive empirical analysis of this interplay in two studies, the second (targets: $N = 189$, informants: $N = 1352$) being a pre-registered replication of the first (targets: $N = 73$, informants: $N = 549$). Using multilevel profile analyses, we investigated how liking and knowing are differentially associated with judgments' normative accuracy (i.e., reflecting actual characteristics of the average target), distinctive accuracy (i.e., reflecting actual characteristics of specific targets), and positivity bias. Statistical effects were largely consistent across two independent validation measures (self-ratings vs. peer-ratings of personality), and across the two studies. Despite being positively correlated with one another, liking and knowing had opposing effects on person judgments: Knowing targets better was associated with greater distinctive and normative accuracy, and with lower positivity bias. In contrast, liking targets more was associated with lower distinctive and normative accuracy, but with greater positivity bias. The findings suggest that person judgments tend to reflect actual target characteristics as well as evaluative bias, and that the relative extents to which they do are predictable from what the perceivers say about their relationships with the targets (i.e., knowing and liking). Directions for future research are discussed.

Keywords: accuracy, positivity bias, person perception, interpersonal relationships, social accuracy model

Differential Associations of Knowing and Liking with Accuracy and Positivity Bias in Person Perception

For decades, theorists have argued that personality judgments do not only reflect the actual characteristics of the persons who are being described (“targets”), but also an evaluation of the targets by those who provide the judgments (“perceivers”) (Kenny, 2004; Leising, Scherbaum, Locke, & Zimmermann, 2015; Peabody, 1967; Saucier, 1994). As for actual characteristics, a person judgment may contain two different kinds of information: the extent to which the target person resembles the average target (“normative accuracy”), and the specific ways in which the present target is different from the average target (“distinctive accuracy”), in terms of how he or she tends to think, feel, and behave. As for evaluation, the very same target may be described more positively (e.g., as “steady”) or negatively (e.g., as “boring”), independent of the target’s actual characteristics. This overall positivity of person judgments will be called “positivity bias” in the following.

The extent to which person judgments are normatively accurate, distinctively accurate, and/or positively biased is likely to depend on two properties of the relationship between the perceiver and the target in particular: on how well the perceiver knows the target, and on how much the perceiver likes the target. Research has shown that accuracy increases with higher knowing (e.g., Borkenau, Mauer, Riemann, Spinath, & Angleitner, 2004; Funder & Colvin, 1988; Kenny, 1994, 2004; Paunonen, 1989), while liking is associated with positivity bias (Leising, Ostrovski, & Zimmermann, 2013). Notably, however, knowing and liking tend to be correlated with one another (Leising, Erbs, & Fritz, 2010), which is probably for at least two reasons: On the one hand, we tend to spend more time with people we like, thus getting to know them better. On the other hand, “mere exposure” to people tends to create more positive attitudes toward them (Montoya, Horton, Vevea, Citkowicz, & Lauber, 2017; Zajonc, 1968). This means that, in close relationships (i.e., with higher liking and higher knowing), people’s

judgments of targets may in fact be more accurate *and* more positively biased at the same time (West & Kenny, 2011; see below). That is, despite their positive correlation with one another, it is quite likely that knowing and liking may have opposing effects on accuracy and bias in person perception. It is thus critically important to study their *unique* associations with distinctive accuracy, normative accuracy and positivity bias. A considerable number of empirical studies have grappled with various combinations of these variables. None, however, has yet attempted to model the interplay of *all* of them comprehensively, which is necessary in order to avoid possible misinterpretations of data. In the present paper, we attempt such a disentangling, applying multilevel profile analyses to two large, independent datasets.

A comprehensive modelling of the interplay of liking and knowing with the two kinds of accuracy and with positivity bias may provide powerful yet parsimonious theoretical explanations across a broad range of content areas and is key to understanding many important person perception phenomena. First, for example, there is an ongoing debate over the meaning of the higher-order factors that have often been found at the top level of factor hierarchies in the realm of normal personality (e.g., Musek, 2007; Pettersson, Turkheimer, Horn, & Menatti, 2012), of psychopathology (e.g., Caspi et al., 2014) and across both (e.g., Oltmanns, Smith, Oltmanns, & Widiger, 2018; Rushton & Irwing, 2011). Given that the vast majority of studies in this field uses only one source of information (usually the targets' self-ratings), the targets' actual characteristics and evaluative bias tend to be confounded in the respective judgments, making it impossible to discern how much each of these potential sources of co-variation contributes to the (higher-order) factors that may emerge. It is therefore crucial to study the relative extents to which person judgments reflect realities about targets, as opposed to evaluative bias, and how these extents vary depending on the relationships between perceivers and targets.

Second, a large body of empirical studies has investigated perceptions of ingroup versus outgroup members, with a focus on judgment similarity (e.g., Boldry, 1999; Kenny, Gomes, & Kowal, 2015; Linville, Fischer, & Salovey, 1989; Ostrom & Sedikides, 1992). This literature, however, is actually quite inconclusive with regard to the circumstances under which outgroup (or ingroup) members will be perceived as being more similar to one another (Ostrom & Sedikides, 1992). The comprehensive modelling that we attempt in the present paper takes into account some of the most important variables in this regard: How much the perceiver knows about the actual differences between the target persons (as opposed to the actual similarities), and how much the perceiver views the targets in similarly positive or negative ways.

Third, measures of personality profile similarity are a popular research tool (e.g., in couples' research; Rogers, Wood, & Furr, 2018), but studies have shown that a considerable proportion of such similarity is owed to the unique influence of liking (Leising et al., 2013). Spouses who like each other, for example, will use positive terms to describe one another, *irrespective* of their actual personalities. The extent to which judgments reflect an overall positive evaluation has often been called a "halo" (Anusic, Schimmack, Pinkus, & Lockwood, 2009; Nisbett & Wilson, 1977; Thorndike, 1920), and a large volume of empirical papers in social psychology address the phenomenon under that name (cf., Gräf & Unkelbach, 2016; Lance, LaPointe, & Fiscaro, 1994). In research using personality profiles, it is particularly important to disentangle the positivity and the descriptive normativity of personality profiles, because these two components contain different kinds of information, despite their often being closely associated (Rogers & Biesanz, 2015). The comprehensive modeling approach that we present here is capable of accounting for a diverse set of person perception phenomena like these using a common language, and may thus help improve on parsimony in the personality and social psychology literature.

Accuracy and Bias

Our model constitutes a multilevel application of West and Kenny's (2011) Truth and Bias model. The Truth and Bias model posits that perceiver judgments of targets may reflect the actual truth about the target persons to some degree ("truth force"), and perceptual bias to some other degree ("bias force"). For example, perceivers' judgments of how "intelligent" targets are may reflect both the targets' actual intelligence (e.g., as measured by a test) and a perceptual bias due to the targets' gender (e.g., women being judged as more/ less intelligent than men). Notably, the relative influences of truth and bias forces are thought of as being conceptually independent, so being more (or less) accurate does not necessarily imply being less (or more) biased. In our own modelling, we adopt this stance, using a "within-participant analysis" (West & Kenny, 2011) by studying perceivers' judgments of targets on *multiple items at once*, and predicting the strength of different kinds of *associations* between such vectors of judgments (i.e., normative accuracy, distinctive accuracy, and positivity bias) from two moderators that capture properties of the relationship between targets and perceivers (i.e., knowing and liking). Also, we use one bias variable (i.e., positivity bias), but two truth variables: the actual characteristics of the average target (i.e., normative accuracy), and the ways in which the particular target at hand actually differs from the average target (i.e., distinctive accuracy).

The question as to what a target's "actual characteristics" are is among the most difficult issues in personality research. It is impossible to study the accuracy of person judgments without having some sense of what "the truth" is, but defining that truth is somewhat arbitrary. Numerous validation criteria have been proposed and used to assess a person's actual characteristics, among them being what the targets say about themselves, what close acquaintances of the target say about them, and more objective measures, such as intelligence test results (Back & Vazire, 2012; Funder, 1995; Hofstee, 1994; Leising & Back, in press; Vazire & Carlson, 2010). However, no validation criterion has ever become

universally accepted as a “gold standard” for measuring people’s true personality, because different personality domains are probably best assessed using different methods (Back, 2017) and different methods have different strength and weaknesses (Vazire, 2010). As an alternative, it has been suggested to use different criteria that complement each other (Back & Nestler, 2016; Funder, 1995), an advice that we follow in the present series of studies. Specifically, we use both the targets’ self-ratings and aggregated ratings of the targets by close acquaintances as validation criteria for “the truth”, and the extent to which judgments of a target by a perceiver converge with the two truth variables (i.e., self-other agreement and consensus) as *proxies* for accuracy. More objective truth measures are not used, in contrast, for two reasons: First, given that we study person perception broadly across many different measurement domains, gathering objective data relating to each of these domains is simply not feasible. Second, there is often a considerable level of arbitrariness in establishing theoretical connections between the items that are used for judging people’s personality (e.g., “nice”, “outgoing”, etc.) and more objective data (e.g., smiling), because the appropriate connections are unknown and thus have to be determined more or less at will by researchers (Leising & Back, in press). For example, is smiling an indicator of Extraversion, or of Agreeableness, or both? Such determinations are unnecessary when measuring judgmental accuracy in terms of how well a given judgment converges with another judgment, as we do in the present study.

The Model Used in the Present Studies

In our model we apply multilevel profile analyses (Biesanz, 2010; Borkenau & Leising, 2016; Furr, 2008) for different reasons. First, multilevel profile analyses make it possible to determine the strength of the association between judgments and a truth or bias variable for each individual dyad of target and perceiver, and then to predict the strengths of these associations from factors that reside within the target, within the perceiver, or within the specific dyad of target and perceiver – in this case liking and knowing. Second, these analyses

enable an inclusion of item characteristics, apart from the extent to which they describe the average target. In the present study, we incorporated ratings of the items' social desirability as an additional predictor and interpreted the regression weight of these ratings as a measure of positivity bias. Finally, multilevel profile analyses are the most appropriate way of analyzing data when one is aiming for broad conclusions regarding person perception in general (i.e., not limited to particular traits). To enable such conclusions, one needs to apply the approach to large and diverse item sets, as we did in the present study. The coefficients emerging from multilevel profile analyses may be interpreted as reflecting the strengths of effects for the average trait (Allik, Borkenau, Hrebickova, Kuppens, & Realo, 2015; Biesanz, 2010, 2018).

The dependent variable in profile analyses consists of a perceiver's judgments of a target on different traits. This perceiver's impression is usually predicted by (at least) a "normative" profile component (comprising the sample means for each item in the profile) and a "distinctive" profile component (comprising a given target's *deviations* from the normative profile) (Biesanz, 2010; Borkenau & Leising, 2016; Furr, 2009). Distinguishing these components from one another is necessary because the similarity of two profiles (e.g., a profile containing the judgments of interest and a profile containing the respective "true" values) is partly accounted for by the simple fact that items tend to have different means (e.g., most persons are described as being more "friendly" than "odd"). Normative profiles capture these average descriptions of targets, while distinctive profiles capture how a given target is described as being *different* from the average person. Furthermore, it is essential to include a profile of rated item desirability in such analyses. The reason is that people tend to describe one another and themselves in positive terms, and not in negative terms (Edwards, 1953). Therefore, normative and positivity profiles are strongly correlated, which is why most previous research treated normative accuracy as basically interchangeable with positivity (Human & Biesanz, 2011; Human, Sandstrom, Biesanz, & Dunn, 2013). However, a recent study (Rogers & Biesanz, 2015) showed that it is necessary to keep the two components

separate, as the normative profile seems to contain at least some information that is independent of social desirability - most likely differences in how much the average person actually shows the behaviors associated with the individual items. Therefore, if – and only if – the normative profile, the individual targets’ distinctive profiles, and the profile of rated item desirability are simultaneously included in an analysis, it becomes appropriate to interpret the associations between these three types of profiles and a given profile of judgments in terms of “pure” normative accuracyⁱ, distinctive accuracy, and positivity bias (while holding the respective other variables constant at their means). In the multilevel profile analyses that we used in the present paper, distinctive accuracy, normative accuracy and positivity bias were determined for each individual judgment of a target by a perceiver. The strengths of the three associations were predicted by how much the perceivers said they knew and liked their respective targets (see below for a detailed model description).

Overview of Previous Research

We will now briefly summarize previous research on the interplay of knowing and liking on the one hand, and accuracy and positivity bias on the other hand.

Associations of Knowing with Accuracy and Positivity Bias

Knowing a target better means having more relevant information about that target. Kenny’s (1994) weighted-average model (WAM; 1994) predicts that more and better information will promote the formation of more individuated impressions of a target, which should result in higher distinctive accuracy (cf., Biesanz, West, & Millevoi, 2007). Similarly, Funder’s Realistic Accuracy Model (RAM; 1995) subsumes greater “information quantity” under “good information” (1995); that is, more information is thought to increase accuracy in person perception. Indeed, research using profile analyses has consistently found evidence that distinctive accuracy increases with the length of acquaintance between perceiver and target (Biesanz et al., 2007) and with the amount of information that the perceiver has about the target (Biesanz & Human, 2010). Likewise, studies using a trait-wise approach showed

that self-other agreement and consensus increase with the level of acquaintance between target and perceiver (e.g., Bernieri, Zuckerman, Koestner, & Rosenthal, 2016; Blackman & Funder, 1998; Borkenau et al., 2004; Funder & Colvin, 1988; Letzring, Wells, & Funder, 2006; Paunonen, 1989).

However, most targets share some of their actual characteristics with the average target, and the extent to which a judgment captures these characteristics is what normative accuracy is about. Whether knowing targets better is associated with higher normative accuracy is unclear, however, because most previous research did not control for positivity bias (i.e., the normative profile and the desirability profile were confounded) (Biesanz et al., 2007; Biesanz & Human, 2010). In fact, two very different associations would be conceivable. On the one hand, there could be a trade-off between distinctive and normative accuracy in the sense that, the more distinctive information about a target is available to a perceiver, the less that perceiver will base his or her judgment on a normative image of the average target (e.g., Biesanz et al., 2007). Thus, better knowing would strengthen distinctive accuracy but reduce normative accuracy. On the other hand, however, it would also be possible that better knowing goes along with greater distinctive *and* normative accuracy, because judgments by more knowledgeable perceivers accurately reflect the ways in which the target is unlike other people *and* the ways in which the target is like other people. Due to methodological limitations of previous studies (most important: the common confounding of normative accuracy and positivity bias), the correct answer is yet unknown. However, the design of the present studies should enable a clear decision in that regard.

Likewise, the relationship between knowing and positivity bias is unknown, because to our knowledge there are no studies investigating this relationship while controlling for liking. For example, it may seem intuitively reasonable to assume that people would have a *neutral* attitude toward others that they have never met before. Empirically, however, it seems that the default stance toward others is moderately positive (e.g., Sears, 1983; Willis &

Todorov, 2006), which may reflect the reasonable expectation that most others might be helpful and not dangerous. If, as posited above, getting to know a target better goes along with greater accuracy (of either kind), then this should be accompanied by a relative decrease in the extent to which judgments reflect the positivity bias. Again, the comprehensive modelling used in the present series of studies should allow for firm conclusions in this regard.

Associations of Liking with Accuracy and Positivity Bias

Now for our second core property of the perceiver-target relationship: liking. Based on previous research one would expect the perceiver's liking of the target to predict the extent to which a personality profile reflects the positivity bias (Human & Biesanz, 2011; Leising et al., 2013; Leising et al., 2015; Zimmermann, Schindler, Klaus, & Leising, 2018). That is, the more (less) the perceiver likes the target, the more (less) he or she will describe that target in a positive manner, *irrespective* of the target's actual characteristics. This is possible because the universe of trait-descriptive terms contains many evaluative terms that enable a more positive or more negative framing of the same actual target characteristics (Anderson, 1968; Peabody, 1967).

With regard to the relationship between liking and accuracy, however, the evidence is somewhat more conflicting, and theoretical reasoning differs as well. Studies found a positive association between liking and distinctive accuracy (Human et al., 2013; Human & Biesanz, 2011), and/or between liking and the normativeness of ratings (Borkenau & Zaltauskas, 2009; Human et al., 2013; Human & Biesanz, 2011; Leising et al., 2010). However, these studies also had some important methodological limitations: First, item desirability was not included as a separate variable, so normative accuracy was most likely confounded with positivity bias (which should be greater for better-liked targets, see above). In fact, we know of only one study that investigated normative and distinctive accuracy while controlling for social desirability: Using both self-ratings and ratings by close others as validation measures, this

study (Zimmermann et al., 2018) found that perceivers whose liking of their targets was experimentally *reduced* (by telling them that the targets disliked them), described these targets in (a) less positive and (b) *more* normative ways. It seems thus likely that the positive effect of liking on normative accuracy that was found in some of previous studies was actually due to the positive relationship between liking and positivity bias. Second, in most previous studies liking and knowing were not clearly separated from one another either (and knowing a target better should improve distinctive accuracy, see above). In the present study, we disentangle all of these effects, by separately including normative accuracy, distinctive accuracy and positivity bias, as well as liking and knowing in our statistical models. Doing so should enable more firm conclusions in regard to the effect of liking on judgmental accuracy.

And yet another factor has to be considered when discussing the possible relationship between liking and accuracy: It may be important whether the perceiver expects that he or she will have to interact with the target in the future, or not. If such interaction is likely, paying close attention to the target's actual characteristics may be more adaptive than not doing so, because one's own future well-being, status, or safety may partly depend on those very characteristics (Fiske & Neuberg, 1990). This may be especially the case for targets one expects to have conflicts with (i.e., disliked ones). In line with this reasoning, Leising et al. (2010) found that ratings by perceivers who did not like their targets were more individuated than ratings by perceivers who liked their targets. Perceivers and targets in this study actually did have real-life relationships with one another, which is quite different from the situation in laboratory studies where perceivers judge targets that they have never met and will probably never meet again, from video, or after brief structured interactions. In these latter cases, lower liking might simply lead to affective disengagement, withdrawal of attention, and, accordingly, to lower distinctive accuracy (Zimmermann et al., 2018). The studies presented here investigate perceivers and targets that actually have some kind of real-world relationships with one another.

Overview of the Current Research

In the present paper, we seek to examine the differential associations of liking and knowing with both normative and distinctive accuracy, as well as with positivity bias in person judgments. The two studies that we present extend previous research in several ways. First, we clearly separate liking and knowing from one another, which allows for examining their respective differential effects. Second, we also control for the rated social desirability of the items. This way, it becomes possible to disentangle normative accuracy and positivity bias, and to examine the differential effects of liking and knowing on each of these variables separately. Third, in addition to self-ratings we also use ratings of the targets by close acquaintances as a second validation measure, in order to be able to draw conclusions that are more generalizable. Fourth, we use two large independent samples with the second study representing a pre-registered replication of the first. Fifth, we aim at maximizing the ranges of the two relationship variables (i.e., liking and knowing), again to enable broader conclusions. This seems necessary because the judges in the typical study were either nominated by the targets themselves (“target-nominated informants”, TNI) (Leising et al., 2010), or assessed the targets after interacting with them in a “first impression” or “getting acquainted” context (e.g., Human & Biesanz, 2011; Rogers & Biesanz, 2015). Both of these approaches come with important restrictions in regard to knowing and liking: Target-nominated informants tend to know their targets extremely well, and to be positively biased towards the targets, even more so than the targets are biased toward themselves (Leising et al., 2010; Leising, Gallrein, & Dufner, 2014). Perceivers in a getting-acquainted-context are naturally limited in the degree to which they may get to know their targets, and strong levels of antipathy are very unlikely to ensue under such circumstances, given common norms of social interaction with strangers. Aiming to broaden the range of liking and knowing, we thus used an alternative approach to recruit informants: In addition to the usual target-nominated informants, we also recruited informants (“group informants”, GI) who knew the same targets from a natural

group context (seminars and student representative groups at a university). One of the crucial advantages of this recruitment strategy lies in the fact that perceivers and targets within such natural groups have to interact with each other more or less on regular bases, while at the same time leaving them considerable freedom to (dis-)like one another, and to (not) get to know each other better (cf., Oltmanns & Turkheimer, 2006). Finally, by studying perceivers and targets who have actual relationships with one another, we improve on ecological validity, especially when compared with studies that use highly controlled encounters between targets and perceivers in the laboratory.

Participants in both studies were of full age and fully informed about the purpose and procedures of the studies before consenting to participate. No experimental manipulation took place, and there was no risk involved of being harmed in any way. The German Research Foundation (DFG) granted Study 2, which in terms of design was largely identical to Study 1, without an additional ethics review.

Study 1

The first study was exploratory in nature. Its main purpose was to establish an optimal statistical modelling approach, as well as the major effects of liking and knowing on distinctive accuracy, normative accuracy and positivity bias. These were later to be replicated in the second study (see below). Study 1 used a sample from a previous study by Gallrein, Weßels, Carlson, and Leising (2016).

Methods

Procedures

Recruitment. We recruited participants from university seminars and groups of student representatives at a German university. Time and resources limited the number of participants that could be recruited. As we did not know about the effectiveness of our new recruitment strategy, there were no a-priori considerations about sample size or power.

Research assistants visited the groups of potential participants and invited them to participate in the study. The potential participants were informed that their participation would imply a willingness to describe other members of the group, or to be described by other members of the group, in an online questionnaire. In addition, they were told that after a screening, some of them would be selected to complete another, more detailed questionnaire about the respective target. Groups were admitted to the study if at least seven members agreed to participate. Eighty-five groups comprising a total number of 889 persons (group size ranged between 7 and 17) met this requirement.

Online Questionnaires. Figure 1 provides an overview of the procedures. The study comprised two major phases. In the first phase, all group members who had agreed to participate received an email containing a link to a short online questionnaire, a personalized code (e.g., S001P01), and a brief description of the most important features of the study. In the online questionnaire, they were asked to indicate whether they had an impression of each of the other group members when reading their full names (name and surname) (*yes/no*). Then they were asked to rate all members of the group whom they had an image of with regard to how well they knew (i.e., knowing) and how much they liked (i.e., liking) them on 4 items each, in a round robin-format. The response scale for these ratings ranged from 1 (*does not apply at all*) to 5 (*applies exactly*). A total of 805 persons completed the first online questionnaire (response rate: 90 %). These participants were compensated with 5 € or 0.5 hours of course credit.

Based on the results of the first questionnaire, the research team attempted to identify one target and up to six informants per group (= “group informants”, GI), to participate in the second phase of the study. Targets were selected by means of an algorithm that aimed at maximizing the variance of the perceivers’ liking and knowing towards each target: Participants were eligible as targets if they had at least two potential informants with low liking (i.e., liking < 3.0) and two potential informants with high liking (i.e., liking > 3.0). If

several persons in a group were eligible as targets, the person with the higher number of potential informants with low liking levels was selected, because such informants are usually harder to recruit. If there were two or more potential targets with the exact same number of potential informants, we selected the one with higher average knowing levels (as reported by their informants), based on the assumption that the average knowing among all participants in the groups would be rather modest. If a target had more than three potential informants with high or low liking, we selected those informants who reported to know the targets best. We excluded groups as a whole when we could not nominate any target by means of the algorithm just described. This led to the exclusion of four groups, resulting in 81 groups whose members we asked to participate in the second phase of the study.

<Insert Figure 1 about here>

The second phase of the study was designed as a one-with-many study (Kenny, Kashy, & Cook, 2006): In each participant group, the same target was to describe himself or herself, and to be described by several informants. The targets were first sent an email containing their personalized code and a link to a second online questionnaire in which they were asked to rate their own personality (i.e., self-reports). In addition, we asked the targets to provide up to three email-addresses of people (target-nominated informants, TNI) who had agreed to also rate the targets' personality. After the targets had completed the second questionnaire, both their TNI and their respective group informants (GI) were also sent an email containing personalized codes and a link to an online questionnaire in which they were asked to rate the personality of the target (i.e., other-reports) within two weeks' time. When group informants did not participate within the designated two weeks despite being reminded, we selected alternative informants using the algorithm described above, if possible. Targets and group informants received another 10 € or 1 hour of course credit for their participation in the second phase. The analyses presented below are based on the data of the second online questionnaire (i.e., self- and other-ratings of personality).

<Insert Table 1 about here>

Sample. We asked participants from 81 groups to participate in the second phase of the study. Groups were included in the analyses when one target and a minimum of two informants per target completed the second online questionnaire. Seventy-three of the 81 groups ultimately met these requirements. When more than six group informants or more than three target-nominated informants per target completed the questionnaire, we removed the ones who completed it last from the dataset. This led to the exclusion of one group informant. The final sample thus consisted of seventy-three targets (female = 38, 4 failed to report sex; age: $M = 23.19$, $SD = 3.45$), as well as 403 group informants (GI; female = 272, 4 failed to report sex; age: $M = 23.54$, $SD = 4.27$). The self-ratings of these targets selected with the algorithm described above did not differ from a sample with no such recruitment algorithm (Leising, Locke, Kurzius, & Zimmermann, 2016) in terms of Big Five personality traits (see Table 1). On average, there were 5.52 group informants per target (range: 3 - 6). Fifty-six of the 73 targets provided contact details for target-nominated informants. One-hundred and forty-six target-nominated informants (female = 78, 9 failed to report sex; age: $M = 30.14$, $SD = 12.73$) completed the online questionnaire (range: 1-3; 2.61 per target who had named at least one TNI).

Measures

Personality Ratings. We assessed self- and other-perceptions of personality with the same broad set of 107 items, which we only slightly reformulated to adapt them to the two different perspectives. Self-perception items began with “I am a person who...” The items for other-perception began with “This is a person who...”, while we specified “this person” by using the respective name in the general instruction that we sent to the informants by email. All items were rated on a 5-point scale ranging from 1 (*does not apply at all*) to 5 (*applies exactly*). The order of the item blocks – with every measure representing a block (e.g., IAL was one block and BFI another; see below) – was randomized, and so was the order of items

within each block, in order to distribute potential effects of fatigue or routine evenly across all items (see Borkenau, Leising, & Fritz, 2014).

To assess personality according to the Big Five model (Goldberg, 1993; John & Srivastava, 1995; McCrae & Costa, 2008), we employed two instruments. First, we used a set of 30 German adjectives compiled by Borkenau and Ostendorf (1998). In this measure, each Big Five factor is assessed by means of six adjectives (e.g., “clever”), three of which have a positive valence, and three of which have a negative valence. Second, we used the German 10-item short version (Rammstedt & John, 2007) of the 44-item Big-Five Inventory (BFI; John, Donahue, & Kentle, 1991), which consists of short sentences (e.g., “Tends to criticize others”). Moreover, we used an abbreviated form (16 items, two per scale, e.g., “shy”) of the Interpersonal Adjective List (IAL; Jacobs & Scholl, 2005) which assesses interpersonal dispositions according to the interpersonal circumplex (IPC) model (Kiesler, 1983; Wiggins, 1979). We also added another fourteen adjectives (e.g., “handsome”) from a large sample of terms collected in a study by Leising, Ostrovski, and Borkenau (2012), to cover additional content not yet covered by the other measures. In order to measure more extreme and possibly maladaptive variants of personality traits, we created 25 personality pathology items (e.g., “Is constantly worried about almost everything”). Finally, we used two relatively broad items to measure the more positive (i.e., “Likes him- or herself very much”) or more negative (i.e., “Is self-critical”) stance that targets may have toward themselves, and the Rosenberg Self-Esteem Scale (RSE; Rosenberg, 1979) to measure targets’ self- and other-perceived self-esteem (10 items, e.g., “I feel that I have a number of good qualities”).

Liking and Knowing. The informants’ self-reported liking and knowing with regard to the targets were assessed twice: Once in the first, round-robin questionnaire (phase 1), and then again in the second, target-specific other-description questionnaire (phase 2). In the first questionnaire, we checked whether the participants knew each other at all (“I know who this person is”, *yes/no*) and then separately assessed liking (e.g., “I like this person very much”)

and knowing (e.g., “I know this person very well”) by means of four items each (see left half of Table 2). The second questionnaire measured liking and knowing again, with the exact same items. The items were presented in randomized orders and rated on a 1 (*does not apply at all*) to 5 (*applies exactly*) scale. For each perceiver, we obtained liking and knowing means by averaging the reported values on the four items assessing liking and knowing, respectively, after having rescaled the two negative items (items 3 and 4 in Table 2). Internal consistencies were very high for both the liking (ICC [2, 4] = .85) and the knowing (ICC [2, 4] = .92) scale. The liking and knowing values used in the analyses presented below are those from phase 2.

<Insert Table 2 about here>

Item Desirability Ratings. Ratings of the items’ social desirability (“to what extent does a description of a person with this item imply a positive or negative evaluation?”) were obtained from a separate group of thirty-one raters (female = 16, 2 failed to report sex) between the age of 20 and 58 ($M = 29.17$, $SD = 9.66$). They were recruited from the personal social network of the first author. All 107 items were rated on a 10-point scale ranging from 1 (*very negative*) to 10 (*very positive*). The items’ average desirability ratings, which had almost perfect reliability (ICC [2, 31] = .99), were used to account for positivity bias.

Statistical Analyses. We applied multilevel modeling to account for the hierarchical structure of our data, with items (Level 1) nested in perceivers (Level 2), and perceivers nested in targets (Level 3). Note that our model can be interpreted as an adaptation of the Social Accuracy Model (SAM; Biesanz, 2010) to the case of a one-with-many design (Kenny et al., 2006), resulting in nested (instead of crossed) random effects for perceivers and targets (random effects for dyads cannot be estimated using a one-with-many design). Following the model of the study by Zimmermann et al. (2018), on Level 1, we predicted the profile containing a perceiver’s impressions of a target from (a) a distinctive validation profile, (b) a normative validation profile, and (c) the profile of rated item desirability. In order to enhance comparability among these three Level 1 predictors, we did a linear transformation of the

desirability profile (which was rated on a 1-10 response scale) to harmonize it with the distinctive and normative profiles (which were rated on 1-5 response scales). We ran two separate analyses to test the same effects, but using different validation measures: In the first model (Model 1.1), we predicted the ratings by the group informants from the ratings by the target-nominated informants, that is, we used the TNI ratings as the validation measure. In the second model (Model 1.2), we predicted all informant-ratings from the targets' self-ratings, that is, we used the targets' self-ratings as the validation measure. Note that all models used in Study 1 are denoted with a "1" (e.g., Model 1.2, for Model 2 in Study 1) in order to distinguish them from the models used in Study 2.

We analyzed the influence of two Level 2 predictors: knowing and liking. We began by first testing the univariate effects of knowing (Model 1.1a and 1.2a) and liking (Model 1.1b and 1.2b) on distinctive accuracy, normative accuracy, and positivity bias, and then tested the partial effects of knowing and liking when entered simultaneously (Model 1.1c and 1.2c). The models were estimated in R 3.4.1 (R Development Core Team, 2017) using the package "lme4" (Bates, Mächler, Bolker, & Walker, 2015). We report *p*-values based on Satterthwaite approximations to degrees of freedom. In addition, we report standardized effect sizes for selected fixed effectsⁱⁱ.

Model 1.1: Target-nominated informant reports as validation measure. In Model 1.1, we predicted the personality profiles reported by the group informants from (a) the distinctive TNI profiles, computed by subtracting the normative TNI profile from the respective raw TNI profiles (averaged across 1-3 TNI per target), (b) the normative profile reported by the target-nominated informants, computed by averaging the average target-nominated informant report per target *across targets*, and (c) the profile of rated item desirability. The full model (1.1c) can be expressed by the following equations:

$$\text{Level 1: } Y_{ipt} = \pi_{0pt} + \pi_{1pt}Dist_{ti} + \pi_{2pt}Norm_i + \pi_{3pt}Des_i + \varepsilon_{ipt}$$

$$\begin{aligned}
\text{Level 2:} \quad \pi_{0pt} &= \beta_{00t} + \beta_{01t} \textit{Liking} + \beta_{02t} \textit{Knowing} + r_{0pt} \\
\pi_{1pt} &= \beta_{10t} + \beta_{11t} \textit{Liking} + \beta_{12t} \textit{Knowing} + r_{1pt} \\
\pi_{2pt} &= \beta_{20t} + \beta_{21t} \textit{Liking} + \beta_{22t} \textit{Knowing} + r_{2pt} \\
\pi_{3pt} &= \beta_{30t} + \beta_{31t} \textit{Liking} + \beta_{32t} \textit{Knowing} + r_{3pt}
\end{aligned}$$

$$\begin{aligned}
\text{Level 3:} \quad \beta_{00t} &= \gamma_{000} + u_{00t} \\
\beta_{01t} &= \gamma_{010} \\
\beta_{02t} &= \gamma_{020} \\
\beta_{10t} &= \gamma_{100} + u_{10t} \\
\beta_{11t} &= \gamma_{110} \\
\beta_{12t} &= \gamma_{120} \\
\beta_{20t} &= \gamma_{200} + u_{20t} \\
\beta_{21t} &= \gamma_{210} \\
\beta_{22t} &= \gamma_{220} \\
\beta_{30t} &= \gamma_{300} + u_{30t} \\
\beta_{31t} &= \gamma_{310} \\
\beta_{32t} &= \gamma_{320}
\end{aligned}$$

with Y_{ipt} being the group-informant (perceiver) p 's rating of target t on item i , $Dist_{ti}$ being the deviation of the average value on item i that the respective target-nominated informants assigned to their specific target t from the normative value, $Norm_i$ being the value on item i that the target-nominated informant assigned to the average target, and Des_i being the rated social desirability of item i . The expected levels of distinctive accuracy, normative accuracy and positivity bias across targets and perceivers with average liking and knowing levels are represented by the fixed effects γ_{100} , γ_{200} , γ_{300} . The expected change in these values due to variations in liking and knowing, respectively, are represented by the fixed effects γ_{110} and γ_{120} for distinctive accuracy, γ_{210} and γ_{220} for normative accuracy, and γ_{310} and γ_{320} for the positivity bias. The random effects r and u represent deviations from the fixed effects that are due to perceivers p and targets t , respectively.

Because of the selection algorithm, targets t did not differ in terms of liking and knowing, so we omitted the respective random effects for the sake of model simplicity. Random effects were assumed to be normally distributed, and allowed to correlate within levels. In order to enhance interpretability, we centered all predictor variables prior to

analysis. In line with recommendations by Biesanz (2010), we centered $Dist_{ti}$ within items by subtracting $Norm_i$ itemwise from the raw profiles (resulting in a grand mean of zero), while $Norm_i$, Des_i and the Level 2 predictors were centered around their respective grand mean. Therefore, each of these effects is interpreted while the respective other predictors are zero, that is, being held constant at their mean levels.

Model 1.2: Self-reports as validation measure. In Model 1.2, we predicted *all* informant reports (both GI and TNI) from (a) the distinctive profile based on targets' self-reports ($Dist_{ti}$), (b) the normative target self-report profile ($Norm_i$), and (c) the item desirability profile (Des_i). Again in line with recommendations by Biesanz (2010), the distinctive profiles ($Dist_{ti}$) were centered within items by subtracting $Norm_i$ itemwise (resulting in a grand mean of zero), while the other predictors were centered around their respective grand mean. In order to account for any other possible differences between the two types of informants (e.g., due to the different recruiting procedures), we also included a dummy-coded variable representing informant type (0 = GI, 1 = TNI) as an additional predictor (*Type*) in each of the four equations at Level 2. The fixed effects γ_{130} , γ_{230} and γ_{330} thus represent the expected change in distinctive accuracy, pure normative accuracy and positivity that is due to the respective rater belonging to a specific informant group. The full model (1.2c) can be expressed by the following equations:

$$\text{Level 1: } Y_{ipt} = \pi_{0pt} + \pi_{1pt}Dist_{ti} + \pi_{2pt}Norm_i + \pi_{3pt}Des_i + \varepsilon_{ipt}$$

$$\begin{aligned} \text{Level 2: } \pi_{0pt} &= \beta_{00t} + \beta_{01t}Liking + \beta_{02t}Knowing + \beta_{03t}Type + r_{0pt} \\ \pi_{1pt} &= \beta_{10t} + \beta_{11t}Liking + \beta_{12t}Knowing + \beta_{13t}Type + r_{1pt} \\ \pi_{2pt} &= \beta_{20t} + \beta_{21t}Liking + \beta_{22}Knowing + \beta_{23}Type + r_{2pt} \\ \pi_{3pt} &= \beta_{30t} + \beta_{31t}Liking + \beta_{32t}Knowing + \beta_{33t}Type + r_{3pt} \end{aligned}$$

$$\begin{aligned} \text{Level 3: } \beta_{00t} &= \gamma_{000} + u_{00t} \\ \beta_{01} &= \gamma_{010} \\ \beta_{02} &= \gamma_{020} \\ \beta_{03} &= \gamma_{030} \\ \beta_{10t} &= \gamma_{100} + u_{10t} \\ \beta_{11t} &= \gamma_{110} \end{aligned}$$

$$\begin{aligned}
\beta_{12t} &= \gamma_{120} \\
\beta_{13t} &= \gamma_{130} \\
\beta_{20t} &= \gamma_{200} + u_{20t} \\
\beta_{21t} &= \gamma_{210} \\
\beta_{22t} &= \gamma_{220} \\
\beta_{23t} &= \gamma_{230} \\
\beta_{30t} &= \gamma_{300} + u_{30t} \\
\beta_{31t} &= \gamma_{310} \\
\beta_{32t} &= \gamma_{320} \\
\beta_{33t} &= \gamma_{330}
\end{aligned}$$

<Insert Table 3 about here>

Results

Liking and knowing. Liking and knowing had a strong correlation with each other across all informants (both GI and TNI), $r_{(549)} = .71, p < .001, 95\% \text{ CI } [.67, .75]$, which is similar to the correlation reported in Leising et al. (2010) ($r = .65$). The distributions of liking and knowing among the group informants were almost normal, with 43.4% of the informants reporting liking and 39.5% reporting knowing values above 3.0. In contrast, 96.6% of the target-nominated informants reported average liking and knowing values above 3.0, respectively. Target-nominated informants reported significantly higher liking ($t(361.56) = -21.46, p < .001, 95\% \text{ CI } [-1.59, -1.32], d = 1.91$) and significantly higher knowing ($t(414.53) = -22.70, p < .001, 95\% \text{ CI } [-1.74, -1.47], d = 1.95$) toward the targets than did the group informants. Means and standard deviations for liking and knowing in the two groups of informants are displayed in the left half of Table 3. Results are in line with previous research reporting that the typical target-nominated informant is a very close acquaintance of his or her target (Leising et al., 2010).

<Insert Table 4 about here>

Model 1.1. The results for Model 1.1 (predicting the group informants' judgments from judgments by the target-nominated informants) are summarized in the left half of Table 4. All three Level 1 predictors had a significant positive effect on the group informants'

judgments, meaning that there was significant distinctive accuracy (γ_{100}), normative accuracy (γ_{200}) and positivity bias in these ratings (γ_{300}). When the Level 2 predictors were entered separately, knowing (Model 1.1a) had significant positive effects on both types of accuracy, and a significant negative effect on positivity. Liking (Model 1.1b) had no significant effect on distinctive accuracy, but significant positive effects on normative accuracy and positivity bias. Some of these associations changed, however, when liking and knowing were entered simultaneously (Model 1.1c): Knowing still had significant positive effects on distinctive (see Figure 2A) and normative (see Figure 3A) accuracy, as well as a negative effect on positivity bias (see Figure 4A). However, liking now had a negative effect on distinctive accuracy (see Figure 2B), whereas the previous positive effect of liking on normative accuracy vanished (see Figure 3B), and the positive association with positivity bias remained (see Figure 4B).

<Insert Figures 2A to 4B about here>

Model 1.2. Results for Model 1.2 are summarized in the right half of Table 4. Here, we predicted all informants' impressions (including GI and TNI) from the targets' self-reportsⁱⁱⁱ. In Model 1.2, the type of informant (*Type*) was included as an additional Level 2 predictor to control for possible differences between the two informant groups (0 = GI, 1 = TNI) beyond liking and knowing. Results for Model 1.2a, with only knowing (and informant type) as a Level 2 predictor, and for Model 1.2b^{iv}, with only liking (and informant type) as a Level 2 predictor, were largely the same as for models 1.1a and 1.1b. The only difference was that now we did not find a significant negative effect of knowing on positivity bias. In both models, distinctive accuracy was somewhat higher for TNIs, as compared to GIs. Only in Model 1.1b was normative accuracy also higher, and positivity bias lower, for TNIs.

When all Level 2 predictors were entered simultaneously (Model 1.2c), knowing was positively associated with both types of accuracy, but negatively associated with the positivity bias. Liking was associated with higher positivity bias, and with lower normative accuracy,

but there was no effect of liking on distinctive accuracy. Finally, informant type had independent effects on the three Level 1 slopes that were weaker, but analogous to the effects of knowing^v.

Discussion

The two analyses incorporating all predictors at once (but using different validation measures) yielded very similar, albeit not identical results. Perfectly in line with theoretical predictions (Funder, 1995; Kenny, 1994) and previous studies (e.g., Biesanz et al., 2007; Biesanz & Human, 2010), knowing was positively associated with distinctive accuracy. That is, the better we say we know a person, the more accurately we will be able to report the *distinctive* characteristics of that person or, to put it differently, what sets this person apart from others. In contrast to previous studies investigating normative accuracy without controlling for positivity bias (Biesanz et al., 2007; Biesanz & Human, 2010), knowing was also associated with higher normative accuracy. That is, the better we say we know a person, the more we will be able to accurately describe that person in line with how the average person actually is. In addition, knowing had a strong negative relationship with positivity bias: The better we say we know a target, the less our description of that target will be positively biased. Note that all of these effects are to be interpreted *independent of liking*.

Also in line with our predictions and previous studies (Human & Biesanz, 2011; Leising et al., 2010; Zimmermann et al., 2018), liking was strongly associated with positivity bias. That is, the more we like a target, the more this will be reflected in the (increasing) positivity of our ratings. With regard to liking and accuracy, however, results were rather mixed. When using ratings by target-nominated informants as our validation measure, we did find a negative effect of liking on distinctive accuracy, but no such effect on normative accuracy. When using the targets' self-ratings as our validation measure, the negative effect of liking on distinctive accuracy was not significant, but there was a significant negative effect on normative accuracy. That is, in the first case ratings of better-liked targets reflected the

distinctive characteristics of the targets less, whereas in the second case such ratings reflected those characteristics less that most targets share with one another. Anyhow, both findings contradict findings from previous studies, in which liking was *positively* associated with distinctive accuracy (Human et al., 2013; Human & Biesanz, 2011; Zimmermann et al., 2018) and/or normative accuracy (Borkenau & Zaltauskas, 2009; Human et al., 2013; Human & Biesanz, 2011; Leising et al., 2010). Part of the explanation for these divergent findings may lie in the fact that most previous studies did not distinguish knowing from liking, and/or positivity from normative accuracy.

Obviously, the type of informant (TNI vs. GI) making the judgment was an additional relevant predictor of both kinds of accuracy, and the positivity bias. Given that these effects were perfectly in line with those of the knowing variable, we speculate that the informant type variable contains additional information about the knowledge of the perceiver that was not covered by our respective four-item rating scale.

Study 2

We pre-registered Study 2 as an attempt to replicate the findings from Study 1 (osf.io/9h6jm/). In Study 2, we used a very similar design, but a substantively bigger sample and a partly different set of personality measures. The dataset also comprises several other measures, which are not relevant to the scope of the present analyses and will thus not be referred to in the following. Based on the results of Study 1, we expected that knowing would be positively related to distinctive accuracy and normative accuracy, and negatively related to positivity bias, across two different validation measures: targets' self-ratings and ratings by target-nominated informants. For liking, we predicted largely the opposite pattern: We clearly expected to corroborate the now well-established association between liking and positivity bias. However, since the findings for the effects of liking on accuracy were slightly

inconsistent across the two validation measures in Study 1, we expected that liking may be negatively – but not positively – associated with distinctive and/or normative accuracy.

Methods

Procedures

Recruitment. Procedures in Study 2 were very similar to those in Study 1 (see Figure 1). As before, we recruited participants from university seminars and groups of student representatives at two German universities. Our original goal was to recruit 350 targets in order to be able to statistically corroborate an effect size of $r = .15$ for a simple correlation between two variables with α (two-tailed) = .05 and $1-\beta = .80$. However, we did not perform a specific a-priori power analysis to estimate the sample size needed for the complex statistical model used in the present study, which is why the sample size calculation reported above can only be seen as a very rough approximation. The requirement for a group to be included in the study was a minimum of six group members willing to participate. Three-hundred and fifty-five groups with a total of 3575 students (group size ranged between 6 and 22) met these requirements.

Online Questionnaires. We asked all group members who had agreed to participate to complete an online questionnaire, using a personalized code to get access. In this first questionnaire, we presented the full names (name and surname) of all other participants from the respective group, and the respondents were asked to indicate whether they had an image of each person (*yes/no*). For every person they said they had an image of, they were then asked to report how well they knew him/her (e.g., “I know this person very well”) and how much they liked him/her (e.g., “I like this person very much”). For these round-robin ratings, they used a response scale ranging from 1 (*does not apply at all*) to 5 (*applies exactly*). Two-thousand eight-hundred and one persons completed the first online questionnaire (response rate: 78 %).

Again, this first phase only served to determine eligible participants for the second phase of the study, in which one target and up to six group informants (GI) were to be identified for each group. The respective algorithm was very similar to the one used in Study 1, except for a few minor adaptations: Participants qualified as potential targets when they had at least two informants with low liking levels and two informants with high liking levels. The respective cutoff was set to 3.5, in order to account for our using a slightly different set of items to assess liking (see below). In addition, in sample 2 informants with low liking levels (which are more rare) were selected first and informants with higher liking levels were then matched as closely as possible to the average knowing level of the former, in order to counteract the strong positive association between the two variables (Leising et al., 2010). This way, we attempted to minimize the average knowing difference between the two groups, and to make liking and knowing more independent of one another. Groups were excluded altogether when no target could be identified by means of the algorithm. This led to the exclusion of 77 groups, resulting in 278 groups whose members we asked to complete the second online questionnaire.

In the second questionnaire, the targets were asked to provide self-reports of their own personality. We also asked them to provide the email-addresses of three people who had agreed to rate their personality (target-nominated informants, TNI). We then contacted both the TNI and the respective group informants (GI) and asked them to provide other-reports of their target's personality, using the same items. Analyses in the present article are based on these self- and other-ratings.

The remuneration protocol in Study 2 comprised two stages. Initially, participants in the first phase (round-robin design) were not compensated for their participation. Targets received 20 €, and group informants entered a lottery with 500 prizes of 20 €, as a reward for completing the second questionnaire (one-with-many design). However, we decided to increase these rewards somewhat, when it became clear that the first remuneration model

would not attract as many participants as we had initially aimed for. Now, all participants were compensated with 5 € for taking part in the round-robin phase of the study. Group informants and targets received another 10 € for completing the second online-questionnaire, and targets received another 10 € for providing the contact details of 1-3 potential TNI. In addition, all participants in Study 2 entered a lottery of 1 x 1000 € and 2 x 500 € as an additional incentive.

Sample. We asked participants from 278 groups to participate in the second phase of the study. Out of these, 189 groups ultimately met the requirements, i.e., one target and two to six group informants per target completed the second online questionnaire. The sample thus consisted of 189 targets (female = 124; age: $M = 22.49$, $SD = 3.48$) and 943 group informants (GI; female = 643; age: $M = 22.62$, $SD = 3.16$). On average, there were 4.99 group informants per target (range: 2 - 6). One hundred and fifty-eight out of the 189 targets provided contact details for potential TNI, and 409 TNI (female = 264; age: $M = 30.01$, $SD = 13.17$) ultimately completed the questionnaire as well (range: 1-3; 2.59 per target who had nominated at least 1 informant). With the exception of Conscientiousness, which was slightly higher in our sample, there were no significant differences in self-reported personality between these targets and a sample of targets from a previous study who had been recruited with no such algorithm in place (Leising et al., 2016) (see Table 1).

Measures

Personality Ratings. As in Study 1, we assessed self- and other-perceptions with the same set of items, which were only slightly rephrased to accommodate the different perspectives (self vs. other). The item set comprised 111 items, most of which were the same as in Study 1. We again used the set of 30 adjectives developed by Borkenau and Ostendorf (1998) and the abbreviated form (16 items) of the German Interpersonal Adjective List (IAL; Jacobs & Scholl, 2005) as measures of personality. We used the 10 items of the Rosenberg Self-Esteem Scale (RSE; Rosenberg, 1979) and the broader item to measure a more self-

critical stance (i.e., “Is self-critical”) again, and we added the Single Item Self-Esteem Scale (SISE, Robins, Hendin, & Trzesniewski, 2001), and the Single Item Narcissism Scale (SINS, Konrath, Meier, & Bushman, 2014). In addition, we slightly revised the 25 items that we had created for measuring personality disorder trait facets in Study 1, and added another 25 such items of our own creation (e.g., “Prefers to be alone than with others”). As a measure of depression, we added the two-item Patient Health Questionnaire (e.g., “Little interest or pleasure in doing things”) (PHQ-2; Löwe, Kroenke, & Gräfe, 2005).

Liking and Knowing. Liking and knowing were assessed with four items each (see the right half of Table 2), both in the round robin phase (to identify targets and informants), and among the informants in the one-with-many phase. We slightly reformulated two of the liking items that we had used in Study 1, in order to enable an assessment of higher levels of antipathy (e.g., “I do not like this person”). All items were rated on a scale ranging from 1 (*does not apply at all*) to 5 (*applies exactly*) and presented in randomized orders. As in Study 1, for each perceiver we averaged the reported values on the four items assessing liking and knowing, respectively, after having rescaled the two negative items (items 3 and 4 in Table 2). Internal consistencies were very high for both the liking ($ICC [2, 4] = .89$) and the knowing ($ICC [2, 4] = .93$) scale.

Item Desirability Ratings. As in Study 1, we used ratings of the items’ social desirability to assess the positivity bias. The items were rated with almost perfect reliability ($ICC [2, 30] = .99$) by a separate group of thirty raters (female = 18, 3 failed to report sex) between the age of 20 and 37 ($M = 25.90$, $SD = 4.14$) whom we recruited via public advertisement and who were compensated with 15 euros for their participation. They used a 10-point scale ranging from 1 (*very negative*) to 10 (*very positive*) for their ratings.

Statistical Analyses. In our attempt to replicate the findings from Study 1, we used the exact same statistical analyses (see the respective description above). In order to distinguish

the models used in Study 2 from the ones used in Study 1, they are denoted with a “2” (e.g., Model 2.1, for Model 1 in Study 2). No other analyses were conducted using this dataset.

Results

Liking and knowing. Liking and knowing had a significant positive association with each other across all informants, $r_{(1352)} = .62, p < .01, 95\% \text{ CI } [.59, .65]$. This correlation is a bit lower than the one in Study 1, most likely because of the slightly modified selection algorithm (see above). As in Study 1, most target-nominated informants reported very high levels of liking and knowing with regard to their targets (see right half of Table 3). Again, the difference between target-nominated informants and group informants in terms of liking ($t(1331.56) = -33.81, p < .001, 95\% \text{ CI } [-1.33, -1.18], d = 1.74$) and knowing ($t(1287.36) = -46.51, p < .001, 95\% \text{ CI } [-1.94, -1.79], d = 2.44$) was significant.

<Insert Table 5 about here>

Model 2.1. The results for Model 2.1 predicting the group informants’ ratings from those by the target-nominated informants are displayed in the left half of Table 5. Again, we found evidence for distinctive accuracy (γ_{100}), normative accuracy (γ_{200}) and positivity of these ratings (γ_{300}). That is, the ratings by the group informants did reflect both the distinctive characteristics of individual targets, as well as characteristics of the average target, as judged by the TNIs. Furthermore, the ratings tended to be positively biased. When Level 2 predictors were entered separately, knowing had significant positive effects on both types of accuracy, but no effect on positivity bias (Model 2.1a). Liking had no significant effect on distinctive or normative accuracy, but it did have a significant positive effect on positivity bias (Model 2.1b). Again, these associations changed somewhat when we entered the two Level 2 predictors simultaneously (Model 2.1c): Knowing still had a positive effect on distinctive (see Figure 2A) and normative (see Figure 3A) accuracy, and now also a negative effect on positivity bias (see Figure 4A). Liking, in contrast, had a negative effect on distinctive accuracy (see Figure 2B) and a positive effect on positivity bias (see Figure 4B).

There also was a negative relationship with normative accuracy, but this relationship just missed the conventional threshold of significance (see Figure 3B)^{vi}.

Model 2.2. Results for Model 2.2 are displayed in the right half of Table 5^{vii}. Again, we included the type of informant as an additional Level 2 predictor (0 = GI, 1 = TNI). In Model 2.2, there was significant distinctive accuracy (γ_{100}), normative accuracy (γ_{200}), and positivity bias (γ_{300}). Results for Model 2.2a^{viii}, with only knowing (and informant type) as a Level 2 predictor, were largely the same as for Model 2.1a (which used a different validation measure). In Model 2.2b, the positive effect of liking on the positivity bias was corroborated again, but now we also found a negative effect of liking on normative accuracy. The negative effect on distinctive accuracy just missed the threshold of significance. In both models, TNIs described their targets with greater normative and distinctive accuracy, but only in Model 2.2b did we also find a significant negative effect of being a TNI (as opposed to a GI) on the positivity bias.

When all predictors were entered simultaneously (Model 2.2c), all six effects that are the focus of the present series of studies became significant. Better knowing was associated with higher distinctive and normative accuracy, and with lower positivity bias. Liking had exactly the opposite effects: It was associated with lower distinctive and normative accuracy, but with a higher positivity bias. Again, being a TNI (as opposed to a GI) had additional effects that were basically identical to the effects of knowing targets better^{ix}.

General Discussion

As Study 2 had the purpose of replicating Study 1, we will now discuss the outcome of both studies alongside each other. It should be obvious that the present series of studies had a number of important strengths, especially when compared to most previous studies in this field: We used two large samples of targets and informants who had real-life relationships with one another, two different strategies for recruiting informants, two different validation

criteria, large and diverse sets of items, and we were largely successful at replicating the results from the first study in another, pre-registered study. The most important strength of the present studies, however, lies in the completeness of the analyses: For the first time, distinctive, normative, and positivity information, as well as liking and knowing (and informant type) were simultaneously included in one comprehensive model. Doing so is necessary in order to disentangle the independent associations of these variables with one another.

Using this approach, we found a clear pattern of associations that was largely consistent across the two studies and across the two validation criteria within each study. The bottom line is surprisingly simple: Person judgments tend to reflect both the actual characteristics of the targets and the perceivers' attitudes toward the targets. This can be said conclusively because we always found clear evidence for distinctive and normative accuracy, as well as for positivity bias. Furthermore, the relative strengths of these influences are well predictable from knowing and liking, as reported by the respective perceiver. Figures 2A to 4B display these effects comprehensively. The figures also show how similar the associations were across the two studies^x. Notably, despite the fact that liking and knowing are strongly correlated, their independent statistical effects on the relative influences of the three Level 1 predictors go in *opposite* directions.

Probably the least exciting finding in this regard is the close correspondence between the perceiver's liking of the target and the extent to which the perceiver's judgment of the target incorporates a positivity bias. Similar findings have been reported several times before (Human & Biesanz, 2011; Leising et al., 2013; Leising et al., 2015; Zimmermann et al., 2018), but the present series is only the second (after Zimmermann et al., 2018) that corroborates this finding while controlling for distinctive and normative accuracy. It was also unsurprising to find that better knowing was associated with greater distinctive accuracy. This finding is well in line with those of previous studies (Biesanz et al., 2007; Biesanz & Human,

2010), and with previous theorizing (Funder, 1995; Kenny, 1994): Better knowing should imply more opportunities for perceivers to observe a target's actual behaviors and thus form an accurate impression about this particular person.

More unexpectedly, we also found that knowing predicts normative accuracy, when controlling for positivity bias. This finding directly contradicts those of previous studies (Biesanz et al., 2007; Biesanz & Human, 2010; Borkenau & Zaltauskas, 2009; Human et al., 2013; Human & Biesanz, 2011), suggesting that in those studies the strong effect of liking (which is correlated with knowing) on positivity bias (which is correlated with profile normativeness) may have overruled the effect of “pure knowing” on “pure normative accuracy”. It has been argued that normative accuracy should be especially high in the initial stages of acquaintance (i.e., when knowing is low), because then the perceiver has little information about the specific characteristics of the target person and may thus draw from an image of the average person as a surrogate. With increasing knowledge, this “stereotypical” image would then be replaced by one that more closely reflects the specifics of the person at hand. According to this view, distinctive accuracy should increase, but normative accuracy should decrease, the more the perceiver knows the target. Our studies clearly confirmed the first prediction, but just as clearly disconfirmed the second. According to our data, it seems thus likely that normative accuracy does not merely reflect the workings of some general heuristic, but rather the processing of actual information about the target person. The better the perceiver knows the target, the more his/her view of the target reflects the target's actual characteristics – the unique ones, and the ones that the target has in common with other targets. The heuristic that perceivers *do* apply in the absence of actual information about targets seems to be *positivity*, as evidenced by the fact that the positivity bias was particularly strong when knowing was low (see Figure 4A). We consistently found medium to strong negative effects of knowing on the positivity bias. This finding supports the idea that people might take a moderately positive “default stance” toward unknown target persons, which then

decreases with the extent to which more information about the actual characteristics of the target become available. Theoretically speaking, such a default stance may be adaptive – on average – to facilitate an approach tendency and initiate interactions with other individuals (Peeters & Czapinski, 1990), because most others are not dangerous but likely to co-operate. The same default stance does, however, pose a certain risk, because some others may actually *be* dangerous. It seems possible that the moderately positive default stance the average person has toward unknown others reflects the most adaptive compromise with respect to these two possible outcomes.

The effects we found for target-nominated informants as compared to group informants were very similar to the associations we found between knowing on the one hand, and distinctive accuracy, normative accuracy and positivity bias on the other. It is thus likely that the differences between the two differently recruited types of informants reflect other aspects of – possibly more intimate – knowing that are not covered by the measure that we used to assess knowing. Future research will need to clarify the nature of these differences.

As of now, research on the association between liking and accuracy has been rather inconclusive. While there are good reasons to expect a negative association between liking and distinctive accuracy, most studies found a positive one instead (Human et al., 2013; Human & Biesanz, 2011; Zimmermann et al., 2018). In stark contrast to that, our two studies rather consistently yielded a negative association. It could seem possible that this discrepancy was due to our much broader item set compared to those used in most prior research focusing on Big Five traits only. However, when repeating our analyses with only Big Five items, we found slightly less consistent (which might be due to the considerable loss of statistical power) yet very similar results that clearly go into the same direction as the results based on the full item set^{xi}. Hence, we see two possible reasons for this discrepancy. First, in contrast to most previous studies, we controlled for knowing (which does have a positive association with distinctive accuracy). Second, other than in the aforementioned studies, we used samples

in which perceivers and targets actually had real-life relationships with one another (even if only relatively loose ones, see below), meaning that a target's behaviors may actually have direct consequences for a perceiver's life (e.g., if both become members of the same student work group). Under such circumstances, it may be adaptive for a perceiver to pay particular attention to the actual features of disliked targets because those features may come to interfere with the perceiver's own goals (Fiske & Neuberg, 1990). This theoretical explanation does require the additional assumption that negative outcomes tend to have a greater significance than positive ones, for which there is ample evidence (e.g., Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Future studies will need to corroborate or refute these assumed mechanisms, especially with regard to the extent that the perceiver's own future safety, happiness and well-being depends on the targets' actual behavior. It would be conceivable, for example, to let perceivers judge targets from video (e.g., Zimmermann et al., 2018), while experimentally manipulating those perceivers' expectation as to whether they will have to collaborate with the targets in the future, or not. Experimentally induced dislike might *improve* accuracy in the first case, but it may easily *reduce* accuracy in the second case, due to affective disengagement.

Finally, it seems necessary to address the question of whether our target sample was sufficiently comparable to the samples that were used in previous studies. This may be an issue because of the algorithm that we used to identify potential targets. This algorithm only allowed a group member to become a target if there were others in the same group who liked him/her *and* others who disliked him/her. It thus seems possible that we recruited a target sample containing an unusual proportion of targets with polarizing personality features (e.g., low agreeableness). Fortunately, this concern could largely be ruled out: We compared the mean personality self-ratings of our two target samples with those from a previous study (Leising et al., 2016) in which no such recruitment algorithm for targets was in place (see Table 1). Neither in terms of means on the five scales contained in Borkenau and Ostendorf's

(1998) adjective set, nor in terms of standard deviations did we find any notable differences between our two samples and the reference sample. The only exception was Conscientiousness, for which we found a small significant difference in our Study 2 sample. In fact, it would make sense if the targets who successfully completed the present study (which required some more effort on their side) were a bit more conscientious than the targets from the previous study.

As mentioned in the introduction, our findings may illuminate other phenomena in personality and social psychology research and we will now briefly discuss how the modeling approach presented here may provide a common framework for conceptualizing possible underlying mechanisms. First, according to our analyses, the extent to which perceivers attribute characteristics to targets depends partly on how positive or negative those attributions will make the targets appear, *irrespective* of how much the target is actually like others, or different from others. The more a perceiver likes her respective target, the more (less) she will attribute positive (negative) characteristics to that target. In a dataset comprising items that differ in social desirability, and perceivers who differ in the attitudes they have toward their respective targets, the interaction between these two kinds of differences will lead to correlations between items (and scales) that are solely based on valence. The reason is that the perceivers' different attitudes will be expressed across items, which will introduce co-variance between judgments on these items. To counteract this effect, one may either (a) have different items or scales be judged by different perceivers whose attitudes toward the targets may be assumed to be uncorrelated, or (b) "neutralize" items by reducing their evaluative "ring" while trying to maintain their factual basis. Both approaches have successfully been used in the past, showing that, to a substantial extent, the so-called "general factor of personality" seems to be based on perceiver attitudes (Bäckström, Björklund, & Larsson, 2009; Danay & Ziegler, 2011; Riemann & Kandler, 2010).

Our modelling approach is also directly relevant in regard to perceptions of in-group versus out-group members, and in particular the relative similarity of such perceptions. Assuming that most items measure real target characteristics as well as evaluative bias, one would expect better knowing to strengthen the influence of the former, and higher liking to strengthen the influence of the latter. The more the members of a group actually differ from one another (as opposed to being all alike), higher knowing (i.e., more information about individual group members) should thus “breed differentiation” in perceptions. Often, people know more about the members of their own ingroup(s), as compared to members of outgroups, which offers a simple explanation for the often observed “outgroup homogeneity effect” (e.g., Linville et al., 1989; Park & Judd, 1990). In contrast, higher liking – which is more common for in-groups than for outgroups – should “breed similarity” in social perceptions. This may result in the *opposite* of an outgroup-homogeneity effect. The actual outcome of such a comparison will depend on how different (versus similar) the people in the different groups actually are, and on what relationships – in terms of liking and knowing – the perceivers have with the targets. To appropriately handle such complexity, it is necessary to disentangle the effects of liking and knowing on the relative extents to which person judgments reflect normative and distinctive target characteristics, as opposed to perceiver attitudes.

Finally, the analyses presented here are directly relevant in regard to the interpretation of measures of profile similarity, which are a popular research tool (e.g., in couples research). As the present study shows, a considerable proportion of profile similarity may be expected to emerge when two perceivers have relatively positive attitudes towards their respective targets (e.g., a husband and his wife describing themselves, or each other), irrespective of the targets’ actual characteristics. Moreover, this similarity is likely to correlate with other measures that at least reflect the same perceiver attitudes (e.g., the couple’s reports of their relationship satisfaction or mental health). Not accounting for such unique effects of

perceiver attitudes bears a substantial risk of misinterpreting data (e.g., that partners who “are” more similar in terms of personality – as evidenced by their more similar personality profiles – have happier relationships).

Limitations

Our studies have several limitations that should be improved on in future research. First, we recruited groups of participants from university classes and student representative groups, in order to overcome an important limitation of previous studies. Most of these studies only used other-ratings by informants who were recruited by the targets, and it has been shown that such informant samples are highly selective in terms of (high) liking and knowing (see above). However, our own recruitment strategy, while successfully overcoming this limitation of previous studies, still resulted in samples that were rather homogenous with regard to other important characteristics, such as age and education level. Future studies should aim for greater diversity in that regard. Second (a related point), even though the participants in our studies did have real-life social relationships with one another, the potential impact they had on each other’s lives may still have been relatively small, as it is rather easy to avoid (e.g., disliked) people in a university context. Future studies should thus consider the extent of mutual interdependence between perceivers and targets more systematically, and possibly even manipulate it experimentally in the laboratory. Third, apart from the extent to which the perceiver likes the target, the perceiver’s perception of how much the target likes him/her (meta-liking) may be also, or even more, important. Despite the typically high mutuality of liking (e.g., Montoya & Insko, 2008) it is still conceivable that a perceiver may not like a target, but think that the target likes him/her. In such cases, the perceiver may expect fewer negative consequences from interacting with the target, and thus be a bit less careful in assessing the target’s actual characteristics. Future studies could explore the moderating role of meta-liking in this regard. Fourth, although we did manage to obtain samples with a relatively high variability on the liking and knowing scales, our items still

captured rather moderate forms of dislike. It is thus unclear whether the results would hold for more extreme forms of dislike (hatred, loathing, contempt). Would informants with such attitudes toward their targets still describe the targets with greater (distinctive) accuracy? Fifth, the knowing variance in our study did not include zero, because people could only take part if they knew each other at least somewhat. Research has shown, however, that the effect of additional information on ensuing impressions is strongest in the early phases of acquaintance (Borkenau et al., 2004). Thus, a more complete picture may be obtained when this first, important phase is covered by one's research design. This is possible both within and outside the lab, but necessarily requires longitudinal assessments.

Sixth, our use of self- and other-ratings of personality as validation criteria entails the possibility that some of the agreement that we found between the different perspectives may have come about by way of the perceivers communicating with one another (possibly agreeing on a wrong impression), not because they independently observed something about the targets that is actually true (Kenny, 1994). This possibility may be addressed by means of laboratory studies in which communication between perceivers is systematically allowed vs. prevented. Finally, our own analyses suggested that the respective type of informant who provided the ratings (TNI vs. GI) played an important role even when controlling for knowing. Its effects, however, were basically identical to those of the knowing variable, which suggests that the ways in which we assess knowing may be in need of further improvement. The simple self-report scales that are currently used in this line of research (including our own study) may not yet adequately cover all of the relevant aspects of this dimension.

Outlook

According to our view, the present series of studies makes a significant contribution to person perception research, by clarifying the specific ways in which two prominent variables that characterize the relationship between perceiver and target (i.e., liking and knowing) are

associated with the degree to which person judgments reflect actual target characteristics as opposed to evaluative bias. Of particular importance in this regard are the opposing directions in which liking and knowing are associated with accuracy and bias, despite their being themselves positively correlated with one another. By highlighting this discrepancy, our paper helps clarify the meaning of the (sometimes overly) broad “acquaintance” factor that was featured prominently in previous research.

Drawing firm conclusions in this regard was possible using multilevel profile analysis, for the reasons outlined in detail above. In our view, the potential of this method has not even been remotely exhausted yet. For example, person descriptors (i.e., items) vary in many more respects than just social desirability (e.g., Leising, Scharloth, Lohse, & Wood, 2014). Some refer to more stable person characteristics than others do, some refer to a broader range of behaviors than others do, and so on. Future research should take these additional types of variation between items into account and investigate how they interact with factors residing in the perceiver, the target, and/or their specific relationship. It seems likely, for example, that perceivers use more “trait-like” terms to describe targets that they have observed for a longer time and/or across more different situations. The model that we presented and tested in this paper may be seen as a comprehensive yet economic account of key mechanisms underlying a broad range of person perception phenomena that are of interest to both personality and social psychologists (e.g., higher-order personality factors, halo, profile similarity, homogeneity vs. heterogeneity in perceptions of ingroup vs. outgroup members). It bears substantial promise for more reliable conclusions in regard to how person judgments jointly reflect characteristics of perceivers, targets, dyads, and items, as well as the ways in which these variables interact with one another.

References

- Allik, J., Borkenau, P., Hrebickova, M., Kuppens, P., & Realo, A. (2015). How are personality trait and profile agreement related? *Frontiers in psychology*, 6, 785. <https://doi.org/10.3389/fpsyg.2015.00785>
- Anderson, N. H. (1968). Likableness ratings of 555 personality-trait words. *Journal of Personality and Social Psychology*, 9(3), 272–279. <https://doi.org/10.1037/h0025907>
- Anusic, I., Schimmack, U., Pinkus, R. T., & Lockwood, P. (2009). The nature and structure of correlations among Big Five ratings: The halo-alpha-beta model. *Journal of Personality and Social Psychology*, 97(6), 1142–1156. <https://doi.org/10.1037/a0017159>
- Back, M. D. (2017). Editorial. *European Journal of Personality*, 31(1), 3–7. <https://doi.org/10.1002/per.2093>
- Back, M. D., & Nestler, S. (2016). Accuracy of judging personality. In J. A. Hall, M. S. Mast, & T. V. West (Eds.), *The social psychology of perceiving others accurately* (pp. 98–124). Cambridge: Cambridge University Press.
- Back, M. D., & Vazire, S. (2012). Knowing our personality. In S. Vazire & T. D. Wilson (Eds.), *Handbook of self-knowledge* (pp. 131–156). Guilford Press.
- Bäckström, M., Björklund, F., & Larsson, M. R. (2009). Five-factor inventories have a major general factor related to social desirability which can be reduced by framing items neutrally. *Journal of Research in Personality*, 43(3), 335–344. <https://doi.org/10.1016/j.jrp.2008.12.013>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, 67(1). <https://doi.org/10.18637/jss.v067.i01>

- Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, 5(4), 323–370. <https://doi.org/10.1037/1089-2680.5.4.323>
- Bernieri, F. J., Zuckerman, M., Koestner, R., & Rosenthal, R. (2016). Measuring Person Perception Accuracy: Another Look at Self-Other Agreement. *Personality and Social Psychology Bulletin*, 20(4), 367–378. <https://doi.org/10.1177/0146167294204004>
- Biesanz, J. C. (2010). The Social Accuracy Model of Interpersonal Perception: Assessing Individual Differences in Perceptive and Expressive Accuracy. *Multivariate behavioral research*, 45(5), 853–885. <https://doi.org/10.1080/00273171.2010.519262>
- Biesanz, J. C. (2018). Interpersonal perception models. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *The SAGE Handbook of Personality and Individual Differences*. Thousand Oaks, CA: Sage Publications.
- Biesanz, J. C., & Human, L. J. (2010). The Cost of Forming More Accurate Impressions: Accuracy-Motivated Perceivers See the Personality of Others More Distinctively but Less Normatively Than Perceivers Without an Explicit Goal. *Psychological Science*, 21(4), 589–594. <https://doi.org/10.1177/0956797610364121>
- Biesanz, J. C., West, S. G., & Millevoi, A. (2007). What do you learn about someone over time? The relationship between length of acquaintance and consensus and self-other agreement in judgments of personality. *Journal of Personality and Social Psychology*, 92(1), 119–135. <https://doi.org/10.1037/0022-3514.92.1.119>
- Blackman, M. C., & Funder, D. C. (1998). The Effect of Information on Consensus and Accuracy in Personality Judgment. *Journal of Experimental Social Psychology*, 34(2), 164–181. <https://doi.org/10.1006/jesp.1997.1347>

- Boldry, J. G. (1999). Intergroup perception in naturally occurring groups of differential status: A social relations perspective. *Journal of Personality and Social Psychology*, 77(6), 1200–1212. <https://doi.org/10.1037/0022-3514.77.6.1200>
- Borkenau, P., & Leising, D. (2016). A More Complete Picture of Personality: What Analyses of Trait Profiles Have Told Us About Personality Judgment--So Far. *Current Directions in Psychological Science*, 25(4), 228–232. <https://doi.org/10.1177/0963721416651960>
- Borkenau, P., Leising, D., & Fritz, U. (2014). Effects of Communication Between Judges on Consensus and Accuracy in Judgments of People's Intelligence. *European Journal of Psychological Assessment*, 30(4), 274–282. <https://doi.org/10.1027/1015-5759/a000188>
- Borkenau, P., Mauer, N., Riemann, R., Spinath, F. M., & Angleitner, A. (2004). Thin slices of behavior as cues of personality and intelligence. *Journal of Personality and Social Psychology*, 86(4), 599–614. <https://doi.org/10.1037/0022-3514.86.4.599>
- Borkenau, P., & Ostendorf, F. (1998). The Big Five as States: How Useful Is the Five-Factor Model to Describe Intraindividual Variations over Time? *Journal of Research in Personality*, 32(2), 202–221. <https://doi.org/10.1006/jrpe.1997.2206>
- Borkenau, P., & Zaltauskas, K. (2009). Effects of self-enhancement on agreement on personality profiles. *European Journal of Personality*, 23(2), 107–123. <https://doi.org/10.1002/per.707>
- Caspi, A., Houts, R. M., Belsky, D. W., Goldman-Mellor, S. J., Harrington, H., Israel, S., . . . Moffitt, T. E. (2014). The p Factor: One General Psychopathology Factor in the Structure of Psychiatric Disorders? *Clinical psychological science*, 2(2), 119–137. <https://doi.org/10.1177/2167702613497473>
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

- Danay, E., & Ziegler, M. (2011). Is there really a single factor of personality? A multirater approach to the apex of personality. *Journal of Research in Personality*, 45(6), 560–567. <https://doi.org/10.1016/j.jrp.2011.07.003>
- Edwards, A. L. (1953). The relationship between the judged desirability of a trait and the probability that the trait will be endorsed. *Journal of Applied Psychology*, 37(2), 90–93. <https://doi.org/10.1037/h0058073>
- Fiske, S. T., & Neuberg, S. L. (1990). A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. *Advances in experimental social psychology*, 23, 1–74.
- Funder, D. C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological review*, 102(4), 652–670.
- Funder, D. C., & Colvin, C. R. (1988). Friends and strangers: Acquaintanceship, agreement, and the accuracy of personality judgment. *Journal of Personality and Social Psychology*, 55(1), 149–158. <https://doi.org/10.1037//0022-3514.55.1.149>
- Furr, M. R. (2009). Profile analysis in person–situation integration. *Journal of Research in Personality*, 43(2), 196–207. <https://doi.org/10.1016/j.jrp.2008.08.002>
- Furr, R. M. (2008). A framework for profile similarity: integrating similarity, normativeness, and distinctiveness. *Journal of Personality*, 76(5), 1267–1316. <https://doi.org/10.1111/j.1467-6494.2008.00521.x>
- Gallrein, A.-M. B., Weßels, N. M., Carlson, E. N., & Leising, D. (2016). I still cannot see it – A replication of blind spots in self-perception. *Journal of Research in Personality*, 60, 1–7. <https://doi.org/10.1016/j.jrp.2015.10.002>
- Gelman, A. (2008). Scaling regression inputs by dividing by two standard deviations. *Statistics in medicine*, 27(15), 2865–2873. <https://doi.org/10.1002/sim.3107>

- Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist*, 48(1), 26–34. <https://doi.org/10.1037//0003-066X.48.1.26>
- Gräf, M., & Unkelbach, C. (2016). Halo Effects in Trait Assessment Depend on Information Valence: Why Being Honest Makes You Industrious, but Lying Does Not Make You Lazy. *Personality & social psychology bulletin*, 42(3), 290–310. <https://doi.org/10.1177/0146167215627137>
- Hofstee, W. (1994). Who should own the definition of personality? *European Journal of Personality*, 8(3), 149–162. <https://doi.org/10.1002/per.2410080302>
- Human, L. J., & Biesanz, J. C. (2011). Through the looking glass clearly: accuracy and assumed similarity in well-adjusted individuals' first impressions. *Journal of Personality and Social Psychology*, 100(2), 349–364. <https://doi.org/10.1037/a0021850>
- Human, L. J., Sandstrom, G. M., Biesanz, J. C., & Dunn, E. W. (2013). Accurate First Impressions Leave a Lasting Impression. *Social Psychological and Personality Science*, 4(4), 395–402. <https://doi.org/10.1177/1948550612463735>
- Jacobs, I., & Scholl, W. (2005). Interpersonale Adjektivliste (IAL). *Diagnostica*, 51(3), 145–155. <https://doi.org/10.1026/0012-1924.51.3.145>
- John, O. P., Donahue, E. M., & Kentle, R. L. (1991). The big five inventory—versions 4a and 54. *Berkeley: University of California, Berkeley, Institute of Personality and Social Research*.
- John, O. P., & Srivastava, S. (1995). The ‘Big Five’ factor taxonomy: History, Measurement, and Theoretical Perspectives. In L. A. Pervin & O. P. John (Eds.), *Handbook of personality: Theory and research* (2nd ed., pp. 102–138). Guilford Press.
- Kenny, D. A. (1994). *Interpersonal perception: A social relations model*. New York: Guilford Press.

- Kenny, D. A. (2004). PERSON: A general model of interpersonal perception. *Personality and Social Psychology Review*, 8(3), 265–280. https://doi.org/10.1207/s15327957pspr0803_3
- Kenny, D. A., Gomes, S. B., & Kowal, C. (2015). The Intergroup Social Relations Model: ISRM. *Group Dynamics: Theory, Research, and Practice*, 19(3), 152–165. <https://doi.org/10.1037/gdn0000028>
- Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic data analysis*. New York: Guilford Press.
- Kiesler, D. J. (1983). The 1982 Interpersonal Circle: A taxonomy for complementarity in human transactions. *Psychological review*, 90(3), 185–214. <https://doi.org/10.1037/0033-295x.90.3.185>
- Konrath, S., Meier, B. P., & Bushman, B. J. (2014). Development and validation of the Single Item Narcissism Scale (SINS). *PloS one*, 9(8), e103469. <https://doi.org/10.1371/journal.pone.0103469>
- Lance, C. E., LaPointe, J. A., & Fisicaro, S. A. (1994). Tests of Three Causal Models of Halo Rater Error. *Organizational Behavior and Human Decision Processes*, 57(1), 83–96. <https://doi.org/10.1006/obhd.1994.1005>
- Leising, D., Gallrein, A.-M. B., & Dufner, M. (2014). Judging the Behavior of People We Know: Objective Assessment, Confirmation of Preexisting Views, or Both? *Personality and Social Psychology Bulletin*, 40(2), 153–163. <https://doi.org/10.1177/0146167213507287>
- Leising, D., & Back, M. D. (in press). Person perception and accuracy. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of personality and individual differences*. New York: Springer.

- Leising, D., Erbs, J., & Fritz, U. (2010). The letter of recommendation effect in informant ratings of personality. *Journal of Personality and Social Psychology*, 98(4), 668–682. <https://doi.org/10.1037/a0018771>
- Leising, D., Locke, K. D., Kurzius, E., & Zimmermann, J. (2016). Quantifying the Association of Self-Enhancement Bias With Self-Ratings of Personality and Life Satisfaction. *Assessment*, 23(5), 588–602. <https://doi.org/10.1177/1073191115590852>
- Leising, D., Ostrovski, O., & Borkenau, P. (2012). Vocabulary for describing disliked persons is more differentiated than vocabulary for describing liked persons. *Journal of Research in Personality*, 46(4), 393–396. <https://doi.org/10.1016/j.jrp.2012.03.006>
- Leising, D., Ostrovski, O., & Zimmermann, J. (2013). “Are We Talking About the Same Person Here?” Interrater Agreement in Judgments of Personality Varies Dramatically With How Much the Perceivers Like the Targets. *Social Psychological and Personality Science*, 4(4), 468–474. <https://doi.org/10.1177/1948550612462414>
- Leising, D., Scharloth, J., Lohse, O., & Wood, D. (2014). What types of terms do people use when describing an individual's personality? *Psychological Science*, 25(9), 1787–1794. <https://doi.org/10.1177/0956797614541285>
- Leising, D., Scherbaum, S., Locke, K. D., & Zimmermann, J. (2015). A model of “substance” and “evaluation” in person judgments. *Journal of Research in Personality*, 57, 61–71. <https://doi.org/10.1016/j.jrp.2015.04.002>
- Letzring, T. D., Wells, S. M., & Funder, D. C. (2006). Information quantity and quality affect the realistic accuracy of personality judgment. *Journal of Personality and Social Psychology*, 91(1), 111–123. <https://doi.org/10.1037/0022-3514.91.1.111>
- Linville, P. W., Fischer, G. W., & Salovey, P. (1989). Perceived distributions of the characteristics of in-group and out-group members: Empirical evidence and a computer

- simulation. *Journal of Personality and Social Psychology*, 57(2), 165–188.
<https://doi.org/10.1037/0022-3514.57.2.165>
- Löwe, B., Kroenke, K., & Gräfe, K. (2005). Detecting and monitoring depression with a two-item questionnaire (PHQ-2). *Journal of psychosomatic research*, 58(2), 163–171.
<https://doi.org/10.1016/j.jpsychores.2004.09.006>
- McCrae, R. R., & Costa, P. T. (2008). A five-factor theory of personality. In O. P. John, R. W. Robins, & P. A. Lawrence (Eds.), *Handbook of Personality, Theory and Research* (3rd ed., pp. 159–181). New York: Guilford Press.
- Montoya, R. M., Horton, R. S., Vevea, J. L., Citkowicz, M., & Lauber, E. A. (2017). A re-examination of the mere exposure effect: The influence of repeated exposure on recognition, familiarity, and liking. *Psychological bulletin*, 143(5), 459–498.
<https://doi.org/10.1037/bul0000085>
- Montoya, R. M., & Insko, C. A. (2008). Toward a more complete understanding of the reciprocity of liking effect. *European Journal of Social Psychology*, 38(3), 477–498.
<https://doi.org/10.1002/ejsp.431>
- Musek, J. (2007). A general factor of personality: Evidence for the Big One in the five-factor model. *Journal of Research in Personality*, 41(6), 1213–1233.
<https://doi.org/10.1016/j.jrp.2007.02.003>
- Nisbett, R. E., & Wilson, T. D. (1977). The halo effect: Evidence for unconscious alteration of judgments. *Journal of Personality and Social Psychology*, 35(4), 250–256.
<https://doi.org/10.1037/0022-3514.35.4.250>
- Oltmanns, J. R., Smith, G. T., Oltmanns, T. F., & Widiger, T. A. (2018). General Factors of Psychopathology, Personality, and Personality Disorder: Across Domain Comparisons. *Clinical psychological science*, 216770261775015.
<https://doi.org/10.1177/2167702617750150>

- Oltmanns, T. F., & Turkheimer, E. (2006). Perceptions of self and others regarding pathological personality traits. In R. F. Krueger & J. L. Tackett (Eds.), *Personality and psychopathology* (pp. 71–111). New York: Guilford Press.
- Ostrom, T. M., & Sedikides, C. (1992). Out-group homogeneity effects in natural and minimal groups. *Psychological bulletin*, 112(3), 536–552. <https://doi.org/10.1037/0033-2909.112.3.536>
- Park, B., & Judd, C. M. (1990). Measures and models of perceived group variability. *Journal of Personality and Social Psychology*, 59(2), 173–191. <https://doi.org/10.1037/0022-3514.59.2.173>
- Paunonen, S. V. (1989). Consensus in personality judgments: Moderating effects of target-rater acquaintanceship and behavior observability. *Journal of Personality and Social Psychology*, 56(5), 823–833. <https://doi.org/10.1037/0022-3514.56.5.823>
- Peabody, D. (1967). Trait Inferences: Evaluative and Descriptive Aspects. *Journal of Personality and Social Psychology*, 7(4), 1–18.
- Peeters, G., & Czapinski, J. (1990). Positive-negative asymmetry in evaluations: The distinction between affective and informational negative effects. In W. Stroebe & M. Hewstone (Eds.), *European review of social psychology* (Vol. 1, pp. 33–60). London: Wiley.
- Pettersson, E., Turkheimer, E., Horn, E. E., & Menatti, A. R. (2012). The General Factor of Personality and Evaluation. *European Journal of Personality*, 26(3), 292–302. <https://doi.org/10.1002/per.839>
- R Development Core Team. (2017). R: A language and environment for statistical computing. Retrieved from <https://www.r-project.org/>

- Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality*, 41(1), 203–212. <https://doi.org/10.1016/j.jrp.2006.02.001>
- Riemann, R., & Kandler, C. (2010). Construct validation using multitrait-multimethod-twin data: The case of a general factor of personality. *European Journal of Personality*, 24(3), 258–277. <https://doi.org/10.1002/per.760>
- Robins, R. W., Hendin, H. M., & Trzesniewski, K. H. (2001). Measuring Global Self-Esteem: Construct Validation of a Single-Item Measure and the Rosenberg Self-Esteem Scale. *Personality and Social Psychology Bulletin*, 27(2), 151–161. <https://doi.org/10.1177/0146167201272002>
- Rogers, K. H., & Biesanz, J. C. (2015). Knowing versus liking: Separating normative knowledge from social desirability in first impressions of personality. *Journal of Personality and Social Psychology*, 109(6), 1105–1116. <https://doi.org/10.1037/a0039587>
- Rogers, K. H., Wood, D., & Furr, R. M. (2018). Assessment of similarity and self-other agreement in dyadic relationships: A guide to best practices. *Journal of Social and Personal Relationships*, 35(1), 112–134.
- Rosenberg, M. (1979). *Conceiving the self*. New York: Basic Books.
- Rushton, J. P., & Irwing, P. (2011). The General Factor of Personality: Normal and Abnormal. In T. Chamorro-Premuzic, S. von Stumm, & A. Furnham (Eds.), *The Wiley-Blackwell handbooks of personality and individual differences* (pp. 132–161). Hoboken, NJ: Wiley-Blackwell.
- Saucier, G. (1994). Separating description and evaluation in the structure of personality attributes. *Journal of Personality and Social Psychology*, 66(1), 141–154. <https://doi.org/10.1037/0022-3514.66.1.141>

- Sears, D. O. (1983). The person-positivity bias. *Journal of Personality and Social Psychology*, 44(2), 233–250. <https://doi.org/10.1037/0022-3514.44.2.233>
- Thorndike, E. L. (1920). A constant error in psychological ratings. *Journal of Applied Psychology*, 4(1), 25–29. <https://doi.org/10.1037/h0071663>
- Vazire, S. (2010). Who knows what about a person? The self–other knowledge asymmetry (SOKA) model. *Journal of Personality and Social Psychology*, 98(2), 281–300. <https://doi.org/10.1037/a0017908>
- Vazire, S., & Carlson, E. N. (2010). Self-Knowledge of Personality: Do People Know Themselves? *Social and Personality Psychology Compass*, 4(8), 605–620. <https://doi.org/10.1111/j.1751-9004.2010.00280.x>
- West, T. V., & Kenny, D. A. (2011). The truth and bias model of judgment. *Psychological review*, 118(2), 357–378. <https://doi.org/10.1037/a0022936>
- Wiggins, J. S. (1979). A psychological taxonomy of trait-descriptive terms: The interpersonal domain. *Journal of Personality and Social Psychology*, 37(3), 395–412. <https://doi.org/10.1037/0022-3514.37.3.395>
- Willis, J., & Todorov, A. (2006). First impressions: Making up your mind after a 100-ms exposure to a face. *Psychological Science*, 17(7), 592–598. <https://doi.org/10.1111/j.1467-9280.2006.01750.x>
- Zajonc, R. B. (1968). Attitudinal effects of mere exposure. *Journal of Personality and Social Psychology*, 9(2, Pt.2), 1–27. <https://doi.org/10.1037/h0025848>
- Zimmermann, J., Schindler, S., Klaus, G., & Leising, D. (2018). The Effect of Dislike on Accuracy and Bias in Person Perception. *Social Psychological and Personality Science*, 9(1), 80–88. <https://doi.org/10.1177/1948550617703167>

ⁱ Please note that, when referring to normative accuracy in the following, we refer to this “pure” form of normative accuracy while controlling for positivity.

ⁱⁱ Standardized effect sizes were calculated based on the formula proposed by Gelman (2008): $d = \frac{2 \cdot \beta \cdot SD_x}{SD_y}$, with d representing the standardized effect size scaled in the metric suggested by Cohen (1988), where $d = 0.2$ is interpreted as a small effect, $d = 0.5$ is interpreted as a medium effect, and $d = 0.8$ is interpreted as a large effect; β representing the unstandardized fixed effect; SD_x representing the standard deviation of the predictor; and SD_y representing the standard deviation of the criterion. When computing standardized effect sizes for, e.g., the effect of liking on distinctive accuracy (i.e., γ_{100}), SD_x corresponds to the standard deviation of liking, estimated from a separate intercept-only model predicting liking. SD_y corresponds to the standard deviation of the random effects of the relevant Level 2 (i.e., π_{1pt}), and Level 3 coefficients (i.e., β_{10t}). This random effect standard deviation was defined as the square root of the sum of the respective random variances (i.e., $VAR(r_{1pt})$ and $VAR(u_{10t})$).

ⁱⁱⁱ There was a strong correlation between the normative profile based on the target’s self-reports, and the normative profile based on the target-nominated informants used in Model 1.1, $r_{(107)} = .961, p < .01, 95\% \text{ CI } [.94, .98]$.

^{iv} Results of this model are based on the “nlminb” optimizer as there were convergence problems when using other optimizers.

^v We conducted additional analyses with a composite validation measure based on targets’ self-reports and target-nominated informant reports (Models 1.3) which support the results found with the two distinct validation measures. As we did not pre-register these analyses, we do not report them in detail here but provide them as additional online material

in our OSF project (osf.io/s5e6m). Please note that results of Model 1.3b are based on the “nlminb” optimizer.

^{vi} Again, we conducted additional analyses with a composite validation measure based on targets’ self-reports and target-nominated informant reports (Models 2.3). The analyses confirm the results of the two distinct validation measures and are available as online material in our OSF project (osf.io/s5e6m).

^{vii} As in Study 1, there was a strong correlation between the normative profile based on the target’s self-reports, and the normative profile based on the TNIs used in Model 2.1, $r_{(111)} = .96, p < .01, 95\% \text{ CI } [.94, .98]$.

^{viii} Results of this model are based on the “nlminb” optimizer as there were convergence problems when using other optimizers.

^{ix} In the course of the review process, it was suggested to test for interaction effects between liking and knowing on distinctive accuracy, normative accuracy, and positivity bias, which we did for each of the full models (Model 1.1c, 1.2c, 2.1c, 2.2c). There were no significant interaction effects for liking and knowing in any of these four models. The results are available as additional material in our OSF project (osf.io/s5e6m).

^x As these associations were also very similar across the two validation measures, displaying another set of six figures for self-ratings as validation measure was considered redundant.

^{xi} These additional analyses based on Big Five items only were suggested during the review process. For detailed results, please see the online material in our OSF project (osf.io/s5e6m).

Figures

Figure 1. Recruitment and data collection procedures.

Figure 2A. Effect of knowing on the unstandardized distinctive accuracy of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Figure 2B. Effect of liking on the unstandardized distinctive accuracy of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Figure 3A. Effect of knowing on the unstandardized normative accuracy of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Figure 3B. Effect of liking on the unstandardized normative accuracy of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Figure 4A. Effect of knowing on the unstandardized positivity of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Figure 4B. Effect of liking on the unstandardized positivity of perceivers' impressions of targets with target-nominated informant ratings as validation measures for Studies 1 and 2.

Tables

Table 1

Results of independent samples t-tests for sample comparisons with reference sample

Variable	Comparison of sample 1 and 3								Comparison of sample 2 and 3							
	Sample 1		Sample 2		Sample 3		<i>t</i>	<i>p</i>	95% CI		Cohen's <i>d</i>	<i>t</i>	<i>p</i>	95% CI		Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>			LL	UL				LL	UL	
Agreeableness	3.824	.641	3.811	.585	3.794	.563	0.352	.726	-.138	.198	0.050	0.291	.771	-.097	.131	0.030
Conscientiousness	3.833	.663	3.868	.557	3.715	.602	1.341	.183	-.057	.294	0.186	2.606	.010	.038	.268	0.264
Extraversion	3.589	.770	3.624	.779	3.535	.796	0.509	.612	-.156	.264	0.069	1.120	.263	-.068	.246	0.113
Emotional Stability	2.927	.691	2.856	.761	2.807	.824	1.204	.231	-.077	.316	0.158	0.612	.541	-.109	.207	0.062
Openness	3.922	.578	3.980	.506	3.958	.489	-0.474	.636	-.187	.115	0.067	0.423	.673	-.078	.121	0.044
<i>N</i>	73		189		201											

Note. The table displays means and standard deviations for targets' self-reports on the Big Five scales measured with 6 items each, as well as the results of independent samples t-tests. Sample 1 = sample used in Study 1. Sample 2 = sample used in Study 2. Sample 3 = reference sample from Leising et al. (2016) used for comparison. Targets in this sample were recruited without any specific selection criteria and are thus used as an example of a "normally recruited" sample. CI = confidence interval. LL = lower limit. UL = upper limit. Cohen's *d* = effect size calculated based on Cohen (1988). *d* = 0.2 is interpreted as a small effect, *d* = 0.5 is interpreted as a medium effect, and *d* = 0.8 is interpreted as a large effect.

Table 2
Scales used to assess liking and knowing

Item no.	Study 1			Study 2		
	<i>German Originals</i>	<i>English translations</i>	<i>Inter-item-correlations</i>	<i>German Originals</i>	<i>English translations</i>	<i>Inter-item-correlations</i>
	Liking		1 2 3	Liking		1 2 3
1	Ich mag diese Person* sehr.	I like this person* very much.		Ich mag diese Person* sehr.	I like this person* very much.	
2	Ich würde fast alles für diese Person* tun.	I would do almost everything for this person*.	.75	Diese Person* ist mir sehr sympathisch.	I find this person* very sympathetic.	.87
3	Ich stehe dieser Person* eher kritisch gegenüber.	I have a rather critical stance towards this person*.	.52 .40	Ich stehe dieser Person* kritisch gegenüber.	I have a critical stance towards this person*.	.56 .61
4	Diese Person* ist nicht gerade mein bester Freund.	I cannot say this person* is my best friend.	.67 .65 .47	Ich kann diese Person* nicht leiden.	I do not like this person*.	.69 .74 .61
ICC	.85			.89		
	Knowing		1 2 3	Knowing		1 2 3
1	Ich kenne diese Person* sehr gut.	I know this person* very well.		Ich kenne diese Person* sehr gut.	I know this person* very well.	
2	Ich kann diese Person* gut einschätzen.	I can assess this person* well.	.77	Ich kann diese Person* gut einschätzen.	I can assess this person* well.	.79
3	Ich weiß wenig über diese Person*.	I know little about this person*.	.84 .79	Ich weiß wenig über diese Person*.	I know little about this person*.	.87 .76
4	Ich weiß, wer diese Person* ist, aber mehr auch nicht.	I know who this person* is, but nothing else.	.70 .67 .73	Ich weiß, wer diese Person* ist, aber mehr auch nicht.	I know who this person* is, but nothing else.	.77 .67 .76
ICC	.92			.93		

Note. * The name of the respective person was specified in the email text. Participants responded all items on a 5-point rating scale, ranging from 1 (*not at all*) to 5 (*very well/very much*). Items no. 3 and 4, respectively, were recoded before computing liking and knowing means per perceiver across the four items. Selected items in Study 2 were slightly reformulated in order to assess stronger antipathy. ICC = internal consistencies of the scales.

Table 3
Means and Standard Deviations for Liking and Knowing

[illegible]

Table 4
Study 1 Social Accuracy Model Results

		TNI-ratings as validation measure				Self-ratings as validation measure			
		Model 1.1a	Model 1.1b	Model 1.1c	<i>d</i>	Model 1.2a	Model 1.2b	Model 1.2c	<i>d</i>
		<i>Estimate (SE)</i>	<i>Estimate (SE)</i>	<i>Estimate (SE)</i>		<i>Estimate (SE)</i>	<i>Estimate (SE)</i>	<i>Estimate (SE)</i>	
Fixed Effects									
Intercept	γ_{000}	2.771*** (0.012)	2.770*** (0.012)	2.770*** (0.012)		2.769*** (0.011)	2.755*** (0.010)	2.76*** (0.010)	
Dist	γ_{100}	0.248*** (0.026)	0.247*** (0.027)	0.245*** (0.026)		0.157*** (0.016)	0.147*** (0.016)	0.155*** (0.016)	
Norm	γ_{200}	0.578*** (0.044)	0.582*** (0.046)	0.579*** (0.044)		0.534*** (0.029)	0.492*** (0.031)	0.525*** (0.029)	
Des	γ_{300}	0.138*** (0.039)	0.143*** (0.039)	0.147*** (0.037)		0.322*** (0.027)	0.399*** (0.025)	0.370*** (0.023)	
Knowing	γ_{020}	0.013 (0.009)		0.032** (0.011)		0.009 (0.008)		0.033*** (0.009)	
Knowing*Dist	γ_{120}	0.049** (0.015)		0.078*** (0.018)	0.605	0.034*** (0.007)		0.042*** (0.009)	0.605
Knowing*Norm	γ_{220}	0.157*** (0.025)		0.156*** (0.030)	0.700	0.136*** (0.018)		0.164*** (0.022)	1.114
Knowing*Des	γ_{320}	-0.055* (0.025)		-0.166*** (0.028)	-0.823	-0.001 (0.019)		-0.145*** (0.020)	-1.012
Liking	γ_{010}		-0.014 (0.010)	-0.033** (0.012)			-0.026** (0.008)	-0.046*** (0.010)	
Liking*Dist	γ_{110}		-0.009 (0.016)	-0.055** (0.019)	-0.394		0.011 (0.008)	-0.015 (0.009)	-0.197
Liking*Norm	γ_{210}		0.101*** (0.028)	0.006 (0.033)	0.025		0.045* (0.021)	-0.054* (0.024)	-0.334
Liking*Des	γ_{310}		0.122*** (0.026)	0.222*** (0.030)	1.017		0.199*** (0.019)	0.286*** (0.022)	1.817
Type	γ_{030}					0.080*** (0.020)	0.132*** (0.020)	0.109*** (0.020)	
Type*Dist	γ_{130}					0.037* (0.018)	0.076*** (0.019)	0.046* (0.019)	0.257
Type*Norm	γ_{230}					0.072 (0.047)	0.225*** (0.048)	0.108* (0.049)	0.284
Type*Des	γ_{330}					0.004 (0.050)	-0.286*** (0.045)	-0.183*** (0.046)	-0.495
Random Effects									
<i>Perceiver variability</i>									
Intercept	$SD(r_{0pt})$	0.133	0.134	0.133		0.134	0.133	0.131	
Dist	$SD(r_{1pt})$	0.191	0.195	0.188		0.106	0.110	0.106	
Norm	$SD(r_{2pt})$	0.323	0.342	0.323		0.288	0.307	0.287	
Des	$SD(r_{3pt})$	0.355	0.338	0.317		0.357	0.320	0.307	
<i>Target variability</i>									
Intercept	$SD(u_{00t})$	0.064	0.062	0.059		0.055	0.003	0.052	
Dist	$SD(u_{10t})$	0.168	0.171	0.163		0.119	0.121	0.118	
Norm	$SD(u_{20t})$	0.282	0.291	0.282		0.177	0.192	0.175	
Des	$SD(u_{30t})$	0.299	0.241	0.224		0.144	0.136	0.114	
Residual	$SD(\varepsilon_{pti})$	0.823	0.823	0.823		0.830	0.830	0.830	

Note. All estimates are based on 107 items. Estimates in Model 1.1 are based on 56 targets and 306 perceivers. Estimates in Model 1.2 are based on 73 targets and 549 perceivers. Dist = Distinctive validation profile. Norm = Normative validation profile. Des = Item social desirability. Type = Informant type (0 = GI; 1 = TNI). *SE* = standard error. *SD* = standard deviation. *d* = standardized effect size. Correlations between random effects were freely estimated but omitted in this table. * $p < .05$, ** $p < .01$, *** $p < .001$

Table 5
Study 2 Social Accuracy Model Results

		TNI-ratings as validation measure				Self-ratings as validation measure			
		Model 2.1a	Model 2.1b	Model 2.1c		Model 2.2a	Model 2.2b	Model 2.2c	
		Estimate (SE)	Estimate (SE)	Estimate (SE)	<i>d</i>	Estimate (SE)	Estimate (SE)	Estimate (SE)	<i>d</i>
Fixed Effects									
Intercept	γ_{000}	2.598*** (0.010)	2.598*** (0.009)	2.597*** (0.009)		2.586*** (0.010)	2.561*** (0.009)	2.567*** (0.009)	
Dist	γ_{100}	0.209*** (0.016)	0.211*** (0.016)	0.208*** (0.016)		0.138*** (0.010)	0.123*** (0.010)	0.134*** (0.010)	
Norm	γ_{200}	0.664*** (0.027)	0.669*** (0.028)	0.664*** (0.027)		0.586*** (0.022)	0.521*** (0.021)	0.572*** (0.021)	
Des	γ_{300}	0.053* (0.024)	0.052* (0.022)	0.056** (0.020)		0.245*** (0.021)	0.335*** (0.017)	0.294*** (0.017)	
Knowing	γ_{020}	-0.026** (0.009)		0.020* (0.009)		-0.027*** (0.008)		0.015* (0.008)	
Knowing*Dist	γ_{120}	0.038*** (0.009)		0.050*** (0.010)	0.357	0.019*** (0.005)		0.026*** (0.006)	0.383
Knowing*Norm	γ_{220}	0.100*** (0.016)		0.114*** (0.017)	0.474	0.088*** (0.013)		0.122*** (0.014)	0.828
Knowing*Des	γ_{320}	-0.011 (0.016)		-0.114*** (0.015)	-0.599	0.014 (0.014)		-0.098*** (0.012)	-0.728
Liking	γ_{010}		-0.114*** (0.008)	-0.122*** (0.009)			-0.109*** (0.007)	-0.115*** (0.008)	
Liking*Dist	γ_{110}		-0.011 (0.009)	-0.030** (0.010)	-0.225		-0.009 (0.005)	-0.019** (0.006)	-0.232
Liking*Norm	γ_{210}		0.016 (0.016)	-0.030 (0.017)	-0.128		-0.041** (0.013)	-0.090*** (0.014)	-0.507
Liking*Des	γ_{310}		0.221*** (0.014)	0.266*** (0.015)	1.453		0.262*** (0.012)	0.301*** (0.013)	1.856
Type	γ_{030}					-0.013 (0.019)	0.073*** (0.015)	0.052** (0.019)	
Type*Dist	γ_{130}					0.062*** (0.013)	0.110*** (0.011)	0.074*** (0.014)	0.420
Type*Norm	γ_{230}					0.087** (0.032)	0.301*** (0.027)	0.136*** (0.032)	0.356
Type*Des	γ_{330}					0.037 (0.035)	-0.263*** (0.025)	-0.131*** (0.030)	-0.375
Random Effects									
<i>Perceiver variability</i>									
Intercept	$SD(r_{0pt})$	0.211	0.187	0.187		0.207	0.190	0.190	
Dist	$SD(r_{1pt})$	0.166	0.168	0.164		0.117	0.118	0.117	
Norm	$SD(r_{2pt})$	0.299	0.309	0.299		0.280	0.285	0.274	
Des	$SD(r_{3pt})$	0.338	0.277	0.267		0.351	0.288	0.282	
<i>Target variability</i>									
Intercept	$SD(u_{00t})$	0.069	0.062	0.060		0.070	0.060	0.059	
Dist	$SD(u_{10t})$	0.182	0.182	0.181		0.113	0.112	0.112	
Norm	$SD(u_{20t})$	0.300	0.313	0.296		0.228	0.234	0.219	
Des	$SD(u_{30t})$	0.240	0.223	0.202		0.192	0.166	0.153	
Residual	$SD(\varepsilon_{pti})$	0.832	0.832	0.832		0.853	0.853	0.853	

Note. All estimates are based on 111 items. Estimates in Model 2.1 are based on 158 targets and 795 perceivers. Estimates in Model 2.2 are based on 189 targets and 1352 perceivers. Dist = Distinctive validation profile. Norm = Normative validation profile. Des = Item social desirability. Type = Informant type (0 = GI; 1 = TNI). *SE* = standard error. *SD* = standard deviation. *d* = standardized effect size. Correlations between random effects were freely estimated but omitted in this table. * $p < .05$, ** $p < .01$, *** $p < .001$