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The Extended Social Relations Model: Understanding Dissimilation and Dissensus in the Judgment of Others

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Abstract

The Social Relations Model (SRM), which has been an important tool for personality researchers, presumes the variabilities in the SRM components, perceiver, target, and relationship effects, are consistent across perceivers and targets. We introduce the extended SRM (eSRM) to examine individual differences in the variances of each component of the SRM. We explore the tendency for perceivers to see targets in different ways, Dissimilation, and the tendency for targets to be viewed in different ways, Dissensus. Furthermore, slopes are used to tap the extent to which perceivers agree with other perceivers, Sensitivity, and the extent to which target judgments depend on how perceivers generally see others, Prototypicality. Moreover, the correlation of a perceiver's judgments with how the target is generally viewed measures Accuracy, and the correlation of judgments of a target with how the perceiver generally views others measures Amplification. Standard deviations assess how a perceiver uniquely views targets, Differentiation, and how a target is uniquely viewed by perceivers, Volatility. A study illustrates the utility of these elements to understand response styles, the accuracy of judgment, and the meaning of SRM effects. The eSRM is discussed in relation to Funder's Realistic Accuracy Model and Biesanz's Social Accuracy Model.

Keywords

interpersonal perception, consensus, assimilation, accuracy, response styles

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The Social Relations Model (SRM) has been an important tool for personality psychologists. In this article, we propose a major extension of the SRM for the study of individual differences. We begin by describing the model and its previous applications by personality psychologists.

The Social Relations Model

In 1986, Malloy and Kenny argued that the Social Relations Model (SRM) is "the correct methodological approach to the study of personality" (p. 201). For studies of social perception, the SRM decomposes social perceptions into three primary components:

1. the perceiver effect or the tendency for a perceiver to see targets in the same way,
2. the target effect or the tendency for a target to be seen in the same way by perceivers, and
3. the relationship effect or the tendency for a perceiver to view a particular target in a certain way.

The formal model (see Kenny, 2019) states for perceiver i's judgment of target j

$$Y_{ij} = m + p_i + t_j + r_{ij} \tag{1}$$

where m is a constant term, p is the perceiver effect, t is the target effect, and r is the relationship effect.[1] In the SRM, the variables p, t and r are random variables whose variances are s_p^2, s_t^2, and s_r^2, respectively.

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Table 1. Hypothetical Ratings Decomposed Using the Social Relations Model.

Perceiver	Target: Alex	Bob	Carl	Dave	Ed	Means	p
Ann	2.95 (1.45)	2.10 (0.10)	1.85 (−0.65)	4.80 (−0.20)	3.30 (−0.70)	3.00	−2.00
Barb	3.50 (0.00)	4.00 (0.00)	4.50 (0.00)	9.00 (2.00)	4.00 (−2.00)	5.00	0.00
Cat	1.65 (−0.85)	4.00 (1.00)	2.65 (−0.85)	6.00 (0.00)	5.70 (0.70)	4.00	−1.00
Dot	4.05 (−1.45)	5.90 (−0.10)	9.15 (2.65)	6.20 (−2.80)	9.70 (1.70)	7.00	2.00
Eve	5.35 (0.85)	4.00 (−1.00)	4.35 (−1.15)	9.00 (1.00)	7.30 (0.30)	6.00	1.00
Means	3.50	4.00	4.50	7.00	6.00	5.00	
t	−1.50	−1.00	−0.50	2.00	1.00		

Note. Perceiver effects, p, in the row margin, target effects, t, in the column margin, and relationship effects in parentheses inside the cells of the table.

As an example of the SRM, consider the hypothetical data in Table 1, in which five female perceivers judge five male targets on how honest they are. SRM perceiver and target effects are in the row and column margins, respectively, and relationship effects are in parentheses next to each entry. Dot tends to see targets as more honest (perceiver effect: 2.00), whereas Ann sees them as less honest (−2.00). We also observe that Dave is seen as most honest (target effect: 2.00), whereas Alex is seen as least honest (−1.50). For the perceiver by target interaction or relationship effect, depicted in parentheses, Dot sees Carl as especially honest (relationship effect: 2.65), whereas Barb sees Ed as especially dishonest (−2.00).

Generally, when personality researchers use the SRM, they study judgments by perceivers of other people's personality. For instance, Paulhus and Reynolds (1995) studied 39 classroom study groups consisting of four to six persons, whose members judged each other's personality on the Big Five. Personality researchers have used all three SRM components to address important theoretical questions.

For example, Kenrick and Funder (1988) argued that perceiver agreement with one another about targets' personalities could be used as evidence to establish the existence of stable individual differences. They argued that such agreement demonstrates that perceptions of personality are more than "in the eye of the beholder." For instance, do Jim and John agree that Marcia is extraverted? Using the SRM, the proportion of variance due to target or $s_t^2/(s_p^2 + s_t^2 + s_r^2)$, called *consensus*, can answer this question, as target variance quantifies the extent to which perceivers agree. Target variance is determined across targets, but can also be interpreted as the similarity of the judgments within a target. Kenny (2019) has estimated that for perceivers who are well acquainted with the target, about 40% of the systematic variance in personality ratings is due to the target. Similar results were also shown by Connelly and Ones (2010). Moreover, several investigators (e.g., Park et al., 1997) have shown that the target effect is remarkably stable over time, with six-month consistencies in the 90s. Together, research has shown that personality judgment is not only based on other people agreeing about a target, but also that people's consensual personality judgments are remarkably stable over time.

The second main component of the SRM, the perceiver effect, has also provided insight into personality judgment, specifically by showing that how people judge others' personalities reveals something about themselves. SRM perceiver variance has been used to assess individual differences in perceivers' tendency to view other people in the same way. For instance, does Jane see others as friendly, whereas Helen sees them as unfriendly? The proportion of perceiver variance or $s_p^2/(s_p^2 + s_t^2 + s_r^2)$ has been called *assimilation*. Perceiver variance is determined across perceivers and can also be interpreted as the similarity of judgments within a perceiver. Kenny (2019) has estimated that about 20% of the systematic variance in personality ratings of long-term acquaintances is due to perceiver, indicating that a sizeable portion of personality judgment depends on the perceivers themselves. Srivastava et al. (2010) have shown that three different factors underlie those chronic tendencies to view others in a certain way: positivity or the general tendency to see others favorably or unfavorably, acquiescence or the general tendency across traits to agree, and trait-specific or unique variance, that is, variance not explained by positivity and acquiescence. For most traits, the dominant source of variance is positivity, followed by trait-specific variance. Recently, Rau et al. (2020) investigated traits and situations that moderate the importance of positivity versus trait-specific variance in determining assimilation. For instance, in terms of the Big Five, positivity is most important for Agreeableness and least important for Extraversion.

As discussed in Malloy and Kenny (1986), relationship variance, called *uniqueness*, has been studied by psychologists who believe the personality interacts with situations or *P x S*. Kenny (2019) estimated that about 40% of variance in ratings of long-term acquaintances is due to the relationship component. Recently, Lakey (2016) has reviewed research in this area and shown that the relationship effect is often

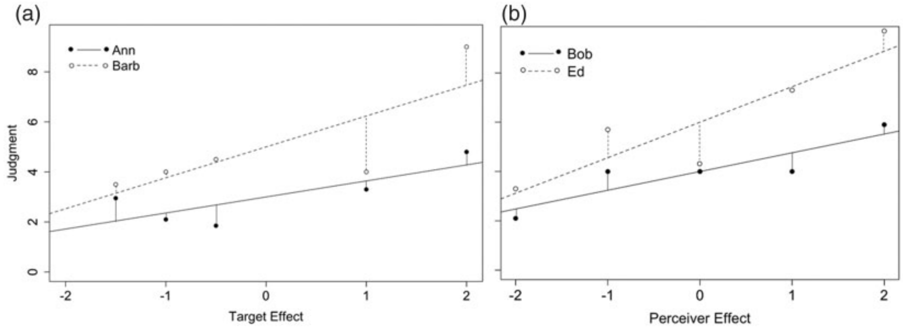

Figure 1. Plots of the Judgments of Two Perceivers. (a) Ann and Barb, as a function of the target effect. (b) Judgments of two targets, Bob and Ed, as a function of the perceiver effect (see Table 1).

the dominant component in social perception. As an example, a recent study of intellectual humility (Meagher et al., 2015), showed high levels of relationship variance, that is, uniqueness. Perceivers do not agree very much on targets' intellectual humility, but instead they see others very idiosyncratically.

A Major Limitation of the SRM

Although the SRM has provided key insights for personality researchers, it has an important limitation, one that is especially relevant for personality psychologists. The model assumes that the importance of a component is the same for all perceivers and targets. Consider a researcher interested in the perception of leadership in groups and seeks to find good judges and targets. The researcher might believe that certain perceivers are especially insightful as to who is a good leader (i.e., Funder's (1995) good judge), whereas others have difficulties recognizing good versus bad leaders. Such good judges should have more target and less relationship variance in their judgments. The researcher also might believe that some targets' leadership is more apparent to perceivers than other targets' leadership (i.e., Funder's (1995) good target), resulting in less perceiver and relationship variance for these targets.

Currently, to test these hypotheses, the researcher needs to have a dichotomous variable that differentiates good and bad perceivers or good and bad targets. For example, to show that women are especially perceptive of leadership, the researcher would have men and women judge a common set of targets and then examine SRM variance separately for each gender. If target variance were higher in the women relative to men group, for example, that would imply that women are more insightful at perceiving leadership than men. However, this strategy would not be viable if the researcher cannot specify an appropriate dichotomous variable or if the variable of interest is not dichotomous. Needed is a generic strategy for studying individual differences among perceivers and targets in the SRM variances. The purpose of this article is to develop a practical strategy for doing so.

To understand individual differences in SRM variances, we return to the data in Table 1. Consider there the five judgments of two perceivers, Ann and Barb. In Figure 1A, we plotted their judgments of the five targets against the estimates of the target effects (i.e., the mean rating of each target minus the grand mean). Contrary to the assumption of the SRM, we see that the slope is much steeper for Barb (1.235) than for Ann (0.641). For Barb, targets judged as very honest by other perceivers are viewed as even more honest by her, whereas for Ann the average ratings by others have less of an effect on her ratings. Figure 1A also shows judgments that deviate from the slopes in Barb and Ann's judgments. These deviations represent relationship effects, because they emerge when the perceiver's rating deviates from the target effect. Note that the standard deviation for Barb's five errors is larger (1.584) than for Ann's five errors (0.810). Barb has more idiosyncratic perceptions of the targets than does Ann.

In Figure 1B, we have also plotted the five judgments for targets Bob and Ed as a function of the perceiver effects. We see that the slope is steeper for Ed (1.440) than for Bob (0.760), meaning that perceivers use their perceiver effect—their default views of others—more in judging Ed relative to judging Bob. Moreover, Ed has a larger standard deviation of errors (1.417) than Bob (0.694). These differences in slopes and deviations from slopes (i.e., relationship effects) for perceivers and targets suggest a violation of the assumption of equal weights in the perceiver, target, and relationship effects in the SRM. The goal of this article is to extend the SRM to allow for individual differences in the use of target, perceiver, and relationship effects.

The Elements of the Extended SRM

In this article, we propose an extended version of the Social Relations Model or extended SRM (eSRM). In building the model, we assume that all perceivers judge the same targets, and all targets are judged by

Table 2. Types of Individual Differences in Disagreement in the Perception of Targets.

Level	Element	Measure	Symbol in model
Perceiver	Dissimilation	Standard deviation of judgments	
	Sensitivity	Slope of target effects predicting judgments	*c*
	Differentiation	Standard deviation of relationship effects	*d*
	Accuracy	Correlation of target effects with judgments	
Target	Dissensus	Standard deviation of judgments	
	Prototypicality	Slope of perceiver effects predicting judgments	*a*
	Volatility	Standard deviation of relationship effects	*v*
	Amplification	Correlation of perceiver effects with judgments	

the same perceivers, as in Table 1. Such a design has been called a *half-block design* (Kenny & La Voie, 1984).

Dissimilation

For perceivers, the SRM focuses on the extent to which a perceiver sees others the same way, that is, Assimilation. However, to focus on individual differences, we must consider how a perceiver sees others differently, what we call *Dissimilation*. It is defined as the within-person standard deviation for each perceiver's judgments (see Table 2), and has been called *intraindividual variability*, but we use the term *Dissimilation* to refer to intraindividual variance when the same stimuli (i.e., targets) are being judged. There is good reason to believe that some of the variance in Dissimilation is due to response set that has been called *extreme response style*[2] or ERS. A response style refers to how someone uses the scale. Baird et al. (2017) documented that intraindividual variability is remarkably consistent in perceiver ratings across many types of judgments. Thus, if Dissimilation was driven by ERS, we should find consistency in Dissimilation scores across traits.

As shown by Liu et al. (2017), the presence of ERS can lead to mistaken conclusions about group differences. Consider a study comparing male and female judgments of targets' attractiveness. Say that we find that females' judgments are more influenced by the age of the targets than are males' judgments. However, if females vary their responses more than males, the restriction in range in the male judgments might lead to a lower correlation for males.

Note, however, that Dissimilation might actually reflect meaningful individual differences among perceivers and be more than a response style. For instance, if a perceiver were more familiar with the targets, it would be reasonable to expect that the perceiver would differentiate the targets more.

Viewed in terms of the SRM, each perceiver's level of Dissimilation emerges for two distinct reasons. First, a given perceiver might match the judgments of other perceivers, whereas another perceiver might not agree very much with other perceivers. We saw this in Figure 1A where Barb's slope was steeper than Ann's slope. We refer to this phenomenon as *Perceiver Sensitivity* or just *Sensitivity*, and it allows for perceiver differences in target variance. Sensitivity can be viewed as a measure of acculturation of the perceiver within the group. Perceivers who have a stronger slope, like Barb in Figure 1A, endorse the group norm more than do other perceivers. Anthropologists (e.g., Romney et al., 1986) have used factor loadings, which are akin to the slopes in Figure 1A, to assess which members of a culture endorse their culture's beliefs more, that is, which members are more knowledgeable informants.

The second SRM source of Dissimilation is due to the fact a perceiver might differentiate targets because of their relationship effect, meaning that they view targets as different from one another but in ways that are unique to that particular perceiver. We saw this in Figure 1A where the spread in Barb's errors was greater than Ann's. We refer to this element as *Perceiver Differentiation*, which allows for perceiver differences in relationship variance. It might be the case that some perceivers have interacted with the targets more and have developed more idiosyncratic views than other perceivers.

An examination of the relation between Sensitivity and Differentiation could provide theoretical insights. Note that high ERS implies that perceivers see targets extremely both systematically as do others, that is, Sensitivity, and randomly, that is, Differentiation. Thus, one way to test whether part of Dissimilation is ERS is to compute the correlation between Sensitivity and Differentiation across perceivers. If the correlation were positive, then there would be support for believing that overall Dissimilation assesses ERS.

Alternatively, there is reason to expect that Sensitivity and Differentiation have a negative correlation: accuracy. Presumably, Funder's (1995) good judge would have a large value for Sensitivity, because it reflects agreement with other judges, and a low value for Differentiation, because it reflects deviations from those consensual judgments. It is reasonable to think that a perceiver who agrees more with other perceivers, that is, has greater Sensitivity, and disagrees less, that is, has lower Differentiation, would be more accurate: Following Funder's (1995) suggestion to use the target effect as a proxy for the truth, we can measure a perceiver's Accuracy as the correlation between the perceiver's judgments and the target effect.

Dissensus

For targets, the SRM focuses on the extent to which a target is seen the same way, that is, Consensus. However, if we are to focus on individual differences, we must consider how a target is viewed differently, what has been called *Dissensus* (Jung, 1999), a measure of intra-target variability or within-target standard deviation. A target having a lower value of Dissensus would imply that perceivers disagree less about the target, making that target a good target.

As with Dissimilation, there are two different aspects of Dissensus. First, the perceiver effect (i.e., average judgments made by a given perceiver) might be used more in judging some targets than others, as in Figure 1B where the perceiver effect was used more for judgments of Ed than for Bob. As seen in Table 1, Dot sees others as more honest than does Ann. In judging Ed, both Dot and Ann default to their standard views of others: Dot sees Ed as more honest than does Ann, by 5.7 points. However, in judging Bob, Dot and Ann do not use their perceiver effects so much and the difference between the two of them is smaller, 2.9 points. The influence of the perceiver effect was stronger for Ed and weaker for Bob. Because this implies that some targets are seen more according to perceivers' general perceptions of others, we refer to this phenomenon as *Target Prototypicality*.

Lower Prototypicality implies greater consensus about the target, which implies a good target. However, the conceptual meaning of Prototypicality is less obvious. Prototypicality implies that for some targets, perceivers use the perceiver effect more than they do for others. What factors would lead perceivers to assimilate one target more than another? One factor might be that there is less information about the target and so perceivers are uncertain and revert to the perceiver effect in making judgments. Another very different view is that the perceiver effect reflects the perceiver's view of the ideal target. Perhaps targets that are more familiar and more liked would be seen as more prototypical.

Alternatively, a target might be seen as very different across perceivers, but in ways that are unique to that particular target. That is, there might be more relationship variance for some targets than for others. We saw in Figure 1B that Ed has a larger relationship variance than Bob, meaning that judgments of Ed are more idiosyncratic than judgments of Bob. We refer to such a phenomenon as *Target Volatility*. Theoretically, Volatility could occur when targets behave differently with different perceivers, targets' behaviors are judged differently by different perceivers, or targets have more error variance.

The meaning of Volatility is straightforward as it refers to the extent to which perceivers disagree about a target and lower Volatility would be evidence of Funder's (1995) good target. Human and Biesanz (2013) found that more socially adjusted persons were easier to judge. There is increasing evidence that good targets are consistently recognized across contexts, time, and domains (Human et al., 2020; Wallace & Biesanz, 2020).

Just as we computed Accuracy as the correlation of a perceiver's judgments with the target effects, we can correlate the judgments of a target with the perceiver effects. We refer to this correlation as *Amplification*, which should be greater as Prototypicality increases and Volatility decreases. Unlike Accuracy, Amplification is not a very intuitive concept, but it might be useful in understanding individual differences.

The eSRM

The Formal Model

The eSRM allows for individual differences in the use of perceiver, target, and relationship effects and the formal model is:

$$Y_{ij} = m + a_j p_i + c_i t_j + r_{ij} \tag{2}$$

where a and c are new parameters, whose means are equal to one and whose variances may be nonzero. Note that when a_j and c_i equal to one, Equation 2 is identical to Equation 1. The a term is a slope parameter, illustrated in Figure 1B, and captures Prototypicality or enhanced vs. reduced Assimilation, and hence we use a to symbolize it; values of a_j greater than one indicate that judgments of target j depend on the perceiver effect more than other targets. The c term is a slope parameter, illustrated in Figure 1B, and captures Sensitivity. Values of c_i greater than one indicate that perceiver i uses the target effect more than do other perceivers or enhanced vs. reduced Consensus, and hence we use c to symbolize it. The relationship variance for perceiver i judging target j or r_{ij} is assumed to equal:

$$ln\left[\sigma^2_{r(ij)}\right] = z + d_i + v_j \tag{3}$$

where d and v have means of zero and nonzero variances and ln is the natural logarithm function (Hedeker et al., 2009). Note that when d_i and v_j are zero, the relationship variance equals a constant of e^z, which is essentially the "average" variance, parallel to the relationship variance or s_r^2 defined in the traditional SRM. The d term captures Differentiation and the v term Volatility. For instance, if perceiver i's value of d were greater than zero, that perceiver would have a greater level of relationship variance than other perceivers; if target j's value of v were greater than zero, that target would have a greater level of relationship variance than other targets. The parameter d is illustrated by how far the points are from the lines in Figure 1A and parameter v is illustrated by how far the points are from the lines in Figure 1B.

Note that various parameters are correlated in the model. Those correlations are for perceivers

p with c: the perceiver effect with Sensitivity,

p with d: the perceiver effect with Differentiation, and

c with d: Sensitivity with Differentiation,

and for targets

t with a: the target effect with Prototypicality,

t with v: the target effect with Volatility, and

a with v: Prototypicality with Volatility.

These correlations may be of substantive interest. In particular, a positive correlation between Sensitivity and Differentiation would suggest a strong ERS effect whereas a negative one would suggest a strong Accuracy effect. Also of interest is the correlation of the target effect with Volatility because it would show whether targets who are evaluated more favorably have more or less consensus. Earlier we defined Accuracy, which is the correlation between t and Y for each perceiver, and Amplification, which is the correlation between p and Y for each target.

Much as is done in a traditional SRM analysis of correlating perceiver and target effects with external variables such as gender, liking, and familiarity, those external variables can be correlated with the eSRM elements. For instance, we might ask the following questions: If a perceiver is more familiar with the targets, does that perceiver show greater Sensitivity? If perceivers are more familiar with a target, does that target have weaker Prototypicality slope?

There is an indeterminacy in the estimation of a and c; that is, one can obtain an infinite number of equally good-fitting solutions with different values of a and c. The difficulty is analogous to the problem of indeterminacy of factor loadings in a rotated two-factor solution. We choose to fix the correlation of Prototypicality or a with the target effect to zero (see Appendix for details). Note that there is no indeterminacy in the estimation of the relationship variance parameters of d and v.

Estimation

Estimation of these eSRM parameters is quite challenging, as the model has heterogeneous slopes due to two latent variables and two sets of heterogeneous variances. We discuss various estimation methods in the Appendix. In this article, we adapt the simple-slope approach that was illustrated earlier in Figure 1. Our approach is preliminary, and we await a more formal estimation method.

Considering first Dissimilation, the judgments by perceiver i are predicted by using the target effects obtained from all perceivers. The equation for perceiver i's judgment of target j or Y_{ij} is

$$Y_{ij} = a_i + b_i T_j + F_{ij} \tag{4}$$

where T_j is defined as the mean rating given to target j minus the grand mean of all ratings given, and this equation is estimated for the n_t judgments of each perceiver and F_{ij} is the error in the regression equation. From that regression analysis, we save the slope of b_i as an estimate of c_i, the Sensitivity of perceiver i. There is a parallel analysis for Dissensus. The equation for Y_{ij}, where i is the perceiver and j is the target, is

$$Y_{ij} = a_i + b_j P_i + F_{ij} \tag{5}$$

where P_i is defined as the mean rating given by perceiver i minus the grand mean of all ratings given and this equation is similarly estimated for the n_p judgments of each target and F_{ij} is the error in the regression equation. From that regression analysis, we save the slope of b_j as a measure of a_j, Prototypicality for target j. We refer to these slopes from these analyses as *simple slopes*.

An adjustment to these simple slopes is required. We focus on Equation 4 and the estimation of c slopes for perceivers, but the concerns also apply to Equation 5 and the estimation of a slopes for targets. To use the slopes from Equation 4 as an estimate of c, we presume that a is uncorrelated with T. If that correlation were nonzero, then the estimates of c would be biased. The problem then is that to estimate the a slopes, we need the c slopes, but to estimate the c slopes, we need a slopes. In the Appendix, we describe a solution for how to arrive at a unique solution by fixing the correlation between a and T to zero.

In addition, to estimate the relationship variance, we cannot use the residuals in Equations 4 and 5. Note that the residual in Equation 4 estimates not the residual or r_{ij} in Equation 2, but also the term of $a_j p_i$. Considering perceiver i and the $a_j p_i$ term, p_i is a constant, making it like a regression coefficient and making a_j or Prototypicality slope like a variable. By a similar logic, the residual in Equation 5 estimates $c_i t_j + r_{ij}$ in Equation 2. To properly compute the variances, we first compute the estimated residuals by subtracting $m + a_j p_i + c_i t_j$ from each score, where p and t can be estimated using the estimated perceiver and target effects, respectively, and the c and a slopes are estimated as described above. To estimate each perceiver's Differentiation, we compute the standard deviation in these residuals for each perceiver; to estimate each target's Volatility, we compute the standard deviation in these residuals for each target (see Appendix for details). Note then that using a standard deviation to measure these parameters means that Differentiation for perceiver i estimates not d_i but rather $\exp(z + d_i)$, and Volatility for target j estimates not v_j but rather $\exp(z + v_j)$, where exp is the exponential function. We could have transformed the variances, but we opted to keep their units in a more interpretable metric of the standard deviation.

Another issue is that the procedure uses estimates of the perceiver and target effects, not the true effects. If there were a sufficient number of perceivers and targets, the estimated perceiver and target effects would have high enough reliability[3] to provide reasonable estimates of the slopes. To obtain reliable estimates of the eSRM elements, there need to be a moderate to large number of both perceivers and targets. The small sample sizes typically used in regular SRM studies, for example, groups of four, would be unable to provide statistically adequate estimates. In implementing the eSRM, we advise researchers to use replication designs to reduce response burden (see Judd et al., 2017). In such designs, targets are first divided into sets, and different groups of perceivers each judge a different set of targets. Each set is a replication of a half block. The example study next discussed uses this design with sets of 20 perceivers and 10 targets.

Earlier, we implied that Dissimilation is a function of Sensitivity and Differentiation. However, as was just discussed in the estimation of relationship variances, there is an additional element: Prototypicality. If a perceiver has a nonzero perceiver effect, some of that perceiver's Dissimilation would reflect variation in the a slopes or Prototypicality. In a parallel fashion, if a target has a nonzero target effect, some of Dissensus would include variation in the c slopes or Sensitivity.

For the eSRM, the correlation between perceiver i's judgments and the target effect can be used as a measure of accuracy (Funder, 1995). Because the perceiver's own judgment is part of the estimated target effect, we remove the perceiver's judgment from the computation of the target effect before computing the correlation. Moreover, if the perceiver's judgments do not vary, we set Accuracy to zero. In a parallel fashion, we compute the correlation between perceivers' judgments of a particular target with the perceiver effect, but we remove that target from the estimate of the perceiver effect.

Our estimation method is preliminary, and eventually a better, though almost certainly more complex, estimation method will be developed. Our purpose in this article is to introduce the eSRM using a relatively simple estimation method and show its utility in the study of individual differences in interpersonal perception.

Example

Method

In this study, 160 participants provided judgments of 40 different targets on 20 different traits. The data were gathered by Jung (1999). Perceivers were University of Connecticut undergraduates who received course credit for participating in the study. Targets were celebrities who were familiar to college students based on a pilot study of 200 celebrities. Traits were taken from Funder et al. (1995) and were unipolar: Talkative, Tough, Gloomy, Inhibited, Enthusiastic, Conceited, Impulsive, Changeable, Boring, Warm, Cheerful, Bold, Rude, Solemn, Cautious, Sloppy, Emotional, Sincere, Nosey, and Intelligent. All ratings were on a 1 to 9 scale, anchored by *not at all* (1), *not very* (3), *moderately* (5), *very* (7), and *extremely* (9). To minimize response burden, the celebrities were divided into four different sets of 10 and traits were divided into two different sets of 10, resulting in eight sets of 20 perceivers judging 10 traits for 10 targets. The design results in each target being judged on each trait by 20 different perceivers, and for each trait, 80 perceivers made judgments.

All 160 perceivers also judged how acquainted they were with each target and how much they liked each target on 9-point scales. We note that although liking and familiarity are often positively correlated, they can have very different effects (Wessels et al., 2020). Perceivers also reported their gender.

Analysis

For each trait, the analysis was conducted within each half block of 20 perceivers and 10 targets and then pooled across the four sets. Where necessary, analyses removed variance due to set by creating dummy variables. Note that this study was not preregistered. The presented analyses are meant to illustrate the eSRM to demonstrate to the reader the possibilities of the eSRM.[4] As the data were gathered 25 years ago, the measures were not chosen with eye to the eSRM. Nonetheless, we report a wide range results to illustrate potential eSRM analyses. The following are the central questions addressed here:

1. What are the correlations between eSRM components and elements?
2. Is there evidence of consistency in eSRM elements across traits?
3. Does the gender of perceivers predict the elements of Dissimilation?
4. Do Familiarity and Liking correlate with the eSRM elements?
5. More generally, is the separation of Dissimilation into Sensitivity and Differentiation and Dissensus into Prototypicality and Volatility necessary?
6. Finally, do we find evidence for Funder's (1995) good judge and good target?

Results

A regular SRM partitioning of variance was conducted. On average, the percentage of perceiver

Table 3. Average Means and Standard Deviations of eSRM Elements Across 20 Traits.

Level	Element	Mean	Standard deviation
Perceiver	Dissimilation	1.867	0.580
	Accuracy	.556	0.281
	Sensitivity	1.000	0.634
	Differentiation	1.450	0.500
Target	Dissensus	1.682	0.365
	Amplification	.369	0.221
	Prototypicality	1.000	0.400
	Volatility	1.450	0.375

Table 4. Correlations Between eSRM Components Averaged Across 20 Traits With the Number of Positive Correlations.

Constructs		*r*	Number +
Target effect (*t*)	Prototypicality (*a*)	–.000[a]	–
	Volatility (*v*)	–.186	5
Perceiver effect (*p*)	Sensitivity (*c*)	–.117	3
	Differentiation (*d*)	–.124	3
Prototypicality (*a*)	Volatility (*v*)	.096	13
Sensitivity (*c*)	Differentiation (*d*)	.179	18

[a]Fixed to zero.

variance was 14.1, target variance was 29.5, and relationship variance was 56.4. These results are comparable to a recent review of 12 long-term acquaintance studies by Kenny (2019). Based on the results in Kenny (2019), about one third of relationship variance is error variance. All of the 20 traits had statistically significant ($p < .05$) perceiver and target variances that were greater than zero.

Descriptive Statistics

Table 3 presents the means and the standard deviations of the eSRM elements averaged across the 20 traits. The average level of Dissimilation (1.87) was larger than the average level of Dissensus (1.68), as well as the average level of Accuracy (.56), which was greater than the average level of Amplification (.37). The greater levels of Dissimilation over Dissensus and Accuracy over Amplification are a necessary consequence of more target than perceiver variance. The means of Sensitivity and Prototypicality are both necessarily constrained to be one, and the means of Differentiation and Volatility are necessarily equal to each other. We note that these eSRM relationship variances for all traits are less than the regular SRM variances, which is to be expected because Sensitivity and Prototypicality are removed from the relationship variances. On average, relationship variances are 7% lower in the eSRM than the SRM. Looking across elements, the comparable standard deviations are always larger for perceivers than for targets, suggesting that there were greater individual differences in eSRM elements for perceivers than for targets.

Do the eSRM Components and Elements Correlate?

We next report the correlations between eSRM components and elements, averaged across the 20 traits. Given our estimation method for the slopes, the correlation of the Target Effect, t, with Prototypicality, a, was fixed to zero. As seen in Table 4, the average correlation of the Perceiver Effect, p, with Sensitivity, c, was $-.117$ with 17 of the 20 correlations being negative. Thus, perceivers with lower perceiver effects had slightly larger Sensitivity values. The average correlation of the Perceiver Effect, p, with Differentiation, d, was $-.124$ with 17 of the 20 correlations being negative. The average correlation of the Target Effect, t, with Volatility, v, was $-.186$ with 15 of the 20 correlations being negative. The average correlation between Prototypicality and Volatility was .096 with 13 of the 20 correlations being positive, which suggests that the two are relatively independent. The average correlation between Sensitivity and Differentiation was .179 with 18 of the correlations being positive, which supports the view that part of Dissimilation is ERS.

Importance of eSRM Elements

We have argued that Dissimilation, or differences in how a perceiver views the targets, is due to Sensitivity and Differentiation and that Dissensus, or differences in how a target is viewed by perceivers, is due to Prototypicality and Volatility. To determine the relative importance of eSRM elements, for the 80 perceivers, we used Sensitivity slopes and Differentiation standard deviations to predict Dissimilation standard deviations in a multiple regression analysis; for the 40 targets, we used Prototypicality slopes and Volatility standard deviations to predict Dissensus standard deviations. Standardized regression coefficients, betas, measured the strength of these effects for each of the 20 traits.[5] For 12 of the 20 traits, Differentiation was more important than Sensitivity with an average beta of 0.623, and for the remaining 8 traits, Sensitivity was more important with an average beta of 0.584. For Dissensus, Volatility was always the most important element with an average beta of 0.779. Prototypicality had lower weight, averaging 0.465.

We also conducted F tests[6] to evaluate whether the variances in the c and a slopes were statistically distinguishable from zero. These analyses were conducted for each trait using the estimated perceiver and target effects as predictors and the perceiver effect slopes varied by target and the target effect slopes varied by perceiver. For Sensitivity, 10 of the 20 traits showed significant differences in the c slopes, whereas for Prototypicality, only 4 of the differences in a slopes were significant. These results, as well as the earlier reported betas, suggest that variation in Sensitivity slopes was more reliable than variation in Prototypicality slopes. Part of the reason for this result is due to the fact that there are more perceivers than targets and also that there is more target than perceiver variance. Both of these factors lead to more reliable estimates of the target effect than the perceiver effect and therefore more reliable estimates of Sensitivity than Prototypicality.

Is There Evidence for Consistency in eSRM Elements Across Traits?

By measuring the consistency of eSRM elements across traits, we can assess whether they measure a construct that affects trait judgments in general or whether they are trait specific. If, for instance, we want to argue that Sensitivity measures the good judge, we would want to see that Sensitivity correlates across different traits. We used the alpha reliabilities for each element to measure consistency. Table 5 gives the alphas, as well as the measured average intertrait correlations. Using .7 as the cutoff for an acceptable level of reliability and .6 for borderline, the levels of reliability for Differentiation and Dissimilation were acceptable, the levels for Dissensus and Amplification were borderline, and levels for the others were poor. Nonetheless, for subsequent correlational analyses, we used the mean score across all traits to reduce the number of correlations to avoid capitalization on chance.

The consistency of Target Prototypicality and Differentiation across different traits can be measured for the two different groups of perceivers who each rated a different set of traits but on the same targets. This can tell us whether a target's Prototypicality and Volatility scores are consistent across traits and perceivers. We therefore correlated mean Prototypicality with mean Volatility across the two sets of traits. The consistency correlation across the two sets of traits for Prototypicality was .026 ($p = .879$) and for Volatility was .325 ($p = .050$). The essentially zero correlation for Prototypicality suggests a lack of consistency across traits.

Table 5. Cronbach's Alpha and Average Intertrait Correlation for eSRM Elements.

Level	Element	Alpha reliability	Average intertrait *r*
Perceiver	Dissimilation	.859	.391
	Accuracy	.448	.093
	Sensitivity	.594	.178
	Differentiation	.798	.302
Target	Dissensus	.607	.140
	Amplification	.659	.154
	Prototypicality	.508	.097
	Volatility	.380	.051

Earlier we examined the correlations of Sensitivity and Differentiation as well as Prototypicality and Volatility by trait. Here we look at those correlations using the means across traits. For Sensitivity and Differentiation, the correlation was .504 ($p < .001$). Earlier, we noted that there were factors that might make the Sensitivity-Differentiation correlation positive (i.e., extreme response style) and other factors that might it negative (i.e., accuracy). The strong positive correlation between average Sensitivity and average Differentiation again provides support for the extreme response style interpretation of Dissimilation. We note that the correlation of average Dissimilation and Accuracy was essentially zero ($r = .082$, $p = .305$), as well the correlation of Amplification and Dissensus ($r = -.251$, $p = .135$). Across targets, we correlated average Prototypicality with average Volatility and the correlation was .023 ($p = .892$). Prototypicality and Volatility were essentially independent, suggesting that they measure something different.

External Correlates of eSRM Elements: Gender, Liking, and Familiarity

We next computed correlations between eSRM elements with external variables. By examining these correlations, we can better understand the construct validity of the eSRM elements.

As seen in Table 6, we correlated gender of the perceiver (coded as 0 for men and 1 for women) with eSRM elements. The correlation with Accuracy was .273 ($p < .001$), consistent with the often-reported finding that women are more accurate perceivers than men (Hall, 1978). Note that gender correlated positively with Sensitivity ($r = .084$, $p = .300$) and negatively with Differentiation ($r = -.167$, $p = .040$). There was little or no correlation between Dissimilation and gender ($-.065$, $p = .422$).

We next examined Familiarity and Liking for each perceiver and used the perceiver effects of Familiarity and Liking—the tendency of the perceiver to say that they were generally familiar with the targets and the tendency to say that they liked all the targets. We conducted a partial correlation analysis to account for collinearity between Familiarity and Liking and these correlations are presented in Table 7. Looking first at perceivers and Dissimilation, we found a statistically significant positive, but weak, correlation for

Table 6. Correlations Perceiver Gender with the eSRM Elements.

Construct	Gender
Dissimilation	–.065
Accuracy	.273*
Sensitivity	.084
Differentiation	–.167*

*$p < .05$.

Table 7. Partial Correlations of eSRM Elements With Familiarity and Liking, Each Controlling for the Other.

Level	Construct	Familiarity	Liking
Perceiver	Dissimilation	.184*	.031
	Accuracy	–.014	.164*
	Sensitivity	.170*	.066
	Differentiation	.169*	–.038
Target	Dissensus	.034	–.585*
	Amplification	.391*	.467*
	Prototypicality	.246	.308+
	Volatility	–.127	–.408*

*$p < .05$. +$p < .10$.

Familiarity ($r = .184$, $p = .023$) and little or no correlation for Liking ($r = .031$, $p = .701$). We note that Familiarity correlated significantly positively with Sensitivity and Differentiation, the two major parts of Dissimilation. Presumably, perceivers who were more familiar with the celebrities varied their responses more than perceivers less familiar with the celebrities because the perceivers knew more about the celebrities. Thus, Dissimilation is not entirely all response set, as Familiarity leads to more variability, both consensual and unique. There appears to be greater accuracy for perceivers who generally liked the celebrities ($r = .164$, $p = .043$), but the relation is weak.

We next examined Familiarity and Liking for each target and used the target effect of Familiarity and Liking—the tendency of a target to be familiar to the perceivers and the tendency for the target to be liked by the perceivers. For Dissensus, we found a substantial negative correlation with Liking ($-.585$, $p < .001$). There is greater consensus for targets who are liked more. Amplification has significant positive correlations with both Familiarity and Liking. Perceivers use their perceiver effects more with targets who were generally familiar and liked. Opposite-signed correlations emerged for both Liking and Familiarity with Prototypicality and Volatility but were larger for Liking. For Prototypicality, the correlation with Liking was positive ($r = .308$, $p = .068$) whereas for Volatility it was negative ($r = -.408$, $p = .014$). The negative correlation for Volatility makes sense in that we would expect less disagreement for celebrities who are liked. The positive correlation with Prototypicality, albeit only marginally significant, is intriguing and is discussed below.

Summary

Consistent with prior literature, there was strong evidence of an extreme response set: Some perceivers use a wide range of scores and others use a narrow range. This tendency is consistent across traits. We find that average Sensitivity and Differentiation were strongly correlated, which also supports the view that part of Dissimilation reflects ERS. However, the finding that perceivers who were very familiar with the celebrities showed greater Dissimilation suggests Dissimilation measures something more than a response style.

The reliability of Accuracy across traits was only .448, but this level is consistent with prior research on individual differences in the accuracy of judgments of personality. For instance, Schlegel et al. (2017) found an average intertrait correlation of .06, whereas we found a somewhat higher value of .10. The level of Accuracy was greater for women than men, $r = .273$. We also find evidence that perceivers who liked the celebrities more were more accurate.

For targets, we investigated Prototypicality, or the extent to which perceivers use the perceiver effect in making judgments of targets, and Volatility, or the extent to which perceivers disagree with one another uniquely. It would seem that lower levels of both tap into Funder's (1995) good target in that they each assess Dissensus. Neither measure showed high levels of intertrait consistency or consistency across judgments of a target on different traits by both the same and different perceivers. Although others (e.g., Human et al., 2020) have found evidence for consistency, this study does not. Perhaps celebrities are different from targets with whom the perceivers interact. Also, these two measures are relatively independent, hardly correlating with each other.

Several sources of evidence point to the measure of Prototypicality having poor construct validity. Besides its already-mentioned low consistency, we found that the element did not significantly vary for a majority of the traits and it explained very little of the variance of Dissensus. Nonetheless, there is evidence, admittedly exploratory, that the component might be meaningful. There is the finding that Liking correlates positively with Prototypicality. We had expected a negative correlation in that more Liking would lead to less use of the perceiver effect. However, we found the opposite, which suggests, very preliminarily, that the perceiver effect might reflect the perceiver's view of the ideal other. Recall that prior literature indicates that two major parts of the perceiver effect are positivity, a general liking or disliking of targets, and trait-specific effects (Rau et al., 2020; Srivastava et al., 2010). If positivity effects were weaker for some targets and stronger for others, we would expect to see consistency across traits in Prototypicality. However, if Prototypicality were due to trait-specific effects, we would expect not to find consistency. Given the relatively low consistency, the tentative implication then is that Prototypicality taps trait-specific effects. We remind the reader that the targets were celebrities and not college students with whom the perceivers interact. Thus, our conclusions about Prototypicality from this study might not be the same as those from studies using peers as targets.

The findings for Volatility are more straightforward. We have already discussed the finding of low consistency across traits for Volatility. In addition, we found that targets who are liked more are also more consensually judged. With apologies to Tolstoy and his description of happy and unhappy families in Anna Karenina, it might be that likeable people are seen the same way, but unlikeable people are seen in very different ways.

The eSRM and the Social Accuracy Model

The Social Accuracy Model or SAM (Biesanz, 2010) has both similarities and differences to the eSRM. SAM takes judgments made by perceivers of multiple targets on multiple traits and computes the slope with the truth (e.g., self-reports or reports by knowledgeable informants) as the predictor and the set of judgments as the outcome. The focus in SAM is on individual differences in these slopes: For instance, SAM measures whether some perceivers are better able to recover the truth, akin to Funder's (1995) good judge, whether some targets are easier to judge, akin to Funder's (1995) good target, and whether some perceiver-target combinations have exceptionally greater accuracy. Similar to SAM, the eSRM allows for individual differences in sensitivity to the truth, but the eSRM operationalizes truth as consensual judgments.

Another major difference is that SAM simultaneously examines relationships across many traits, that is, multivariate, whereas the eSRM is univariate and examines one trait at a time. A third difference is that SAM allows for individual differences in accuracy but assumes that errors are homogeneous with respect to perceiver, targets, and traits. Because the eSRM explicitly allows for both perceivers and targets to have different relationship variances, accuracy depends on both the slope and the relationship variance, with weaker relationship variance leading to higher accuracy.

Overall, we view the eSRM as not so much an alternative to SAM but rather a complement to it. Perhaps, eSRM analyses might be conducted before undertaking a SAM analysis. The eSRM analysis would indicate the relative levels of perceiver, target, and relationship variances, as well as how much these variances differed for perceivers and targets. For instance, if the eSRM analysis indicated effects due to Sensitivity, the suggestion might be that there are perceiver differences in accuracy.

Limitations

One major limitation of our analyses is the confounding of true relationship and error components. In principle, we could have separated the two, but that would require different measures and increase the complexity of an already complex presentation. By not making this separation, the meanings of Differentiation and Volatility are ambiguous. For Differentiation, a true relationship effect implies that nonconsensual views of targets vary more because some perceivers actually see more differences between targets and error implies that some perceivers randomly vary their guesses more than do others. For Volatility, a true relationship effect implies that a target is seen differently by perceivers because for some targets, perceivers have very different views of them, and error implies that some targets generate more errors than do others. Note that Kenny (2019) found that for acquainted dyads, about one third of combined relationship variance and error variance is the error variance.

A second limitation is the need to develop estimates that are derived from a formal statistical model. We outline such a model in the Appendix, but we know of no way currently to estimate the parameters of that model. Once that difficulty is overcome, we would have a way of testing whether there is meaningful variation in each of the elements. With our modified simple regression estimates, we do not know if the variation is meaningful or just due to chance. For instance, in our analyses, we have evidence of problems with Prototypicality, but we do not know if variation in that measure is meaningful or is primarily just due to chance.

A third limitation is that estimates of Sensitivity, or c, and Prototypicality, or a, are not unique. In order to have a unique solution for them, a constraint needs to be made. For our example study, we constrained the correlations between Prototypicality slopes and target effects to be zero. Given the evidence for Prototypicality differences in our study is weak or even nonexistent, this assumption may not be problematic in this case. We do note that correlation of the simple a slopes and the adjusted a slopes averaged across the 20 traits was .911. Thus, the effect of the adjustment, at least for this dataset, was not excessive. We also note that although there are identification issues for the slopes, there are not identification issues for the variances, Differentiation and Volatility. Certainly, future analytic work needs to be undertaken to provide more insight into this identification issue.

A fourth limitation is that we have exclusively focused on the half-block design with no missing data. However, very often peer ratings use a round-robin design in which group members all rate each other. Even when the half block design is used, there often are missing data. Ideally, once a more formal estimation procedure for the eSRM is developed, the round-robin design could be analyzed using the eSRM. However, we expect that round robins would need to have larger numbers of participants than those that are conventionally employed.

Lastly, there is a possible elaboration of the eSRM that we wish to mention. One assumption of the eSRM is that perceiver and target effects are each unidimensional. Consider the case of target effects. Perhaps the target effect for men and women perceivers differs. In such a case, the dimensionality of target effects would be two, not one. A parallel argument could be made for perceiver effects. Ideally there would be a test for unidimensionality and if not met, further modifications of the eSRM would be made.

We have several suggestions to those considering an eSRM analysis at this time. First, we strongly recommend using the half-block design. Second, one needs to ensure that there are a sufficient number of both perceivers and targets, perhaps by using a replication design, that is, multiple half blocks with different perceivers and targets. Third, there should be some perceiver and target variance in the measure; we suggest a minimum of 10%. Fourth, measure plausible perceiver and target predictors of the eSRM elements to elucidate their meaning. Fifth, unless there have been software developments for the estimation of the eSRM, adapt the R code that we have written (see Note 4). Sixth, if there are multiple traits, measure the consistency of the eSRM components across the traits. Seventh, as we have illustrated in the example, there are a multitude of eSRM results. Ideally, concentrate on a few key predictions to investigate.

In addition, all of our discussion and examples have targets as persons. However, targets might be situations or nonsocial objects. For instance, perceivers may be presented with a variety of situations and be asked to appraise how stressful each was. In such a case, the meaning of the different elements would change. For instance, Sensitivity can be viewed as a person's stress reactivity.

Conclusion

Biesanz (2018) has argued that there is no single componential model of interpersonal perception that can address all of the questions that researchers may ask. There needs to be a variety of tools to address different questions and the availability of those tools limit and constrain the questions that can be asked and the insights that can be achieved. This article considers one of those models, the SRM. For 40 years, SRM research has advanced the understanding of social perception. However, it is not well suited to individual differences. For instance, it is difficult to show that SRM target and relationship variances are larger or smaller for some perceivers than for others. In this article, we address that limitation conceptually, statistically, and empirically.

Conceptually, we have argued that that disagreement and agreement are not opposites. The SRM focuses on agreement, both Assimilation and Consensus, but it can be beneficial to consider also disagreement. We have examined a perceiver's disagreement about targets, called Dissimilation, and a perceiver's disagreement about a target, called Dissensus. For Dissimilation, we can examine perceiver differences in consensual agreement, or Sensitivity, and perceiver differences in idiosyncratic disagreement, or Differentiation; for Dissensus, we can examine target differences in assimilation, or Prototypicality, and target differences in idiosyncratic disagreement among perceivers, or Volatility. The eSRM allows for a highly nuanced view of disagreement.

Empirically, we present results from a study that illustrates the utility of the eSRM. Evidence is presented that ERS affects judgments, and there is also evidence that women's judgments are more accurate than men's. Moreover, Familiarity and Liking generally have positive relationships with Prototypicality and negative ones with Volatility.

Statistically, we have developed a formal model that contains the four new elements of the SRM. Although we have yet to derive parametric estimates of that model, we have used a modified regression approach, and have shown how these estimates relate to the formal model. We are optimistic that a creative scholar will very soon develop a practical procedure to estimate the eSRM.

In sum, we believe that the eSRM should prove useful to personality and social psychologists who seek to better understand social perception. We invite others to make statistical and empirical contributions to this topic.

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Notes

1. As explained in numerous sources (e.g., Kenny, 2019), error and relationship variance are confounded when there is only a single judgment by the perceiver of the target. Thus, when we say *relationship variance* in this article, we mean *relationship plus error variance*.
2. Many studies operationalize ERS as the percentage of time that a perceiver uses the most extreme response category. Note that we are simply using the standard deviation across targets for each perceiver.

3. For the perceiver effect, the reliability is $s_p^2/(s_p^2 + s_r^2/n_t)$ where n_t is the number of targets and for the target effect, the reliability is $s_t^2/(s_t^2 + s_r^2/n_p)$ where n_p is the number of perceivers.
4. The data and the R Markdown file are available at https://osf.io/gkt8b/.
5. As explained earlier, the perceiver effect explains some of the variation in Dissimilation and the target effect explains Dissensus. We included these effects as predictors in these regression equations, and they explained less variance than the other eSRM elements.
6. In these analyses, we entered the perceiver and target effects as predictors and allowed the perceiver effect to interact with dummy variables for target and the target effect with dummy variables for perceiver. In testing the perceiver interactions, we controlled for the target interactions, and in testing the target interactions, we controlled for the perceiver interactions.
7. An R Markdown file is available at https://osf.io/m2zn4/, which illustrates the computation of the results.

References

Baird, B. M., Lucas, R. E., & Donnellan, M. B. (2017). The role of response styles in the assessment of intraindividual personality variability. *Journal of Research in Personality*, *69*, 170–179. https//doi.org/10.1016/j.jpr.2016.16.015

Biesanz, J. C. (2010). The social accuracy model of interpersonal perception: Assessing individual differences in perceptive and expressive accuracy. *Multivariate Behavioral Research*, *45*, 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* (pp. 519–534). Sage.

Brunton-Smith, I., Sturgis, P., & Leckie, G. (2017). Detecting and understanding interviewer effects on survey data by using a cross-classified mixed effects location–scale model. *Journal of the Royal Statistical Society A*, 551–568. https://rss.onlinelibrary.wiley.com/doi/full/10.1111/rssa.12205

Connelly, B. S., & Ones, D. S. (2010). An other perspective on personality: Meta-analytic integration of observers' accuracy and predictive validity. *Psychological Bulletin*, *136*, 1092–1122. https://doi.org/10.1037/a0021212

Funder, D. C. (1995). On the accuracy of personality judgment: A realistic approach. *Psychological Review*, *102*, 652–670. https://doi.org/10.1037/0033-295X.102.4.652

Funder, D. C., Kolar, D. C., & Blackman, M. C. (1995). Agreement among judges of personality: Interpersonal relations, similarity, and acquaintanceship. *Journal of Personality and Social Psychology*, *69*, 656–672. https://doi.org/10.1037/0022-3514.69.4.656

González, J., De Boeck, P., Tuerlinckx, F. (2008). A double-structure structural equation model for three-mode data. *Psychological Methods*, *13*, 337–353. https://doi.org/10.1037/a0013269

Hall, J. A. (1978). Gender effects in decoding nonverbal cues. *Psychological Bulletin*, *85*, 845–857. https://doi.org/10.1037/0033-2909.85.4.845

Hedeker, D., Mermelstein, R. J., Berbaum, M. L., & Campbell, R. T. (2009). Modeling mood variation associated with smoking: An application of a heterogeneous mixed-effects model for analysis of ecological momentary assessment (EMA) data. *Addiction*, *104*, 297–307. https://doi.org/10.1111/j.1360-0443.2008.02435.x

Hehman, E., Sutherland, C. A. M., Flake, J. K., & Slepian, M. L. (2017). The unique contributions of perceiver and target characteristics in person perception. *Journal of Personality and Social Psychology*, *113*, 513–529. https://doi.org/10.1037/pspa0000090

Human, L. J., & Biesanz, J. C. (2013). Targeting the good target: An integrative review of the characteristics and consequences of being accurately perceived. *Personality and Social Psychology Review*, *17*, 248–272. https://doi.org/10.1177/1088868313495593

Human, L. J., Rogers, K. H., & Biesanz, J. C. (2020). In-person, online, and up-close: The cross-contextual consistency of expressive accuracy. *European Journal of Personality*, *35*, 120–148. https://dx.doi.org/10.1002/per.2272

Judd, C. M., Westfall, J., & Kenny, D. A. (2017). Experiments with more than one random factor: Designs, analytic models, and statistical power. *Annual Review of Psychology*, *68*, 601–625.

Jung, T. (1999). A new look at moderator variables of agreement: The role of target standing (Order No. 9906550) [Doctoral dissertation]. ProQuest Dissertations and Theses Global.

Kenny, D. A. (2019). *Interpersonal perception: The foundation of social relationships* (2nd ed.). Guilford Press.

Kenny, D. A., & La Voie, L. (1984). The social relations model. In L. Berkowitz (Ed.), *Advances in experimental social psychology* (*Vol. 18*, pp. 142–182). Academic.

Kenrick, D. T., & Funder, D. C. (1988). Profiting from controversy: Lessons from the person-situation debate. *American Psychologist*, *43*, 23–34. https://10.1037/0003-066X.43.1.23

Lakey, B. (2016). Understanding the P×S aspect of within-person variation: A variance partitioning approach. *Frontiers in Psychology*, *7*, Article 2004. https://doi.org/10.3389/fpsyg.2015.02004

Liu, M., Harbaugh, A. G., Harring, J. R., & Hancock, G. R. (2017). The effect of extreme response and non-extreme response styles on testing measurement invariance. *Frontiers in Psychology*, *8*, Article 726. https//doi.org/10.3389/fpsyg.2017.00726

Malloy, T. E., & Kenny, D. A. (1986). The social relations model: An integrative method for personality research. *Journal of Personality*, *54*, 199–225. https//doi.org/10.1111/j.1467-6494.1986.tb00393.x

Maydeu-Olivares, A., & Coffman, D. L. (2006). Random intercept item factor analysis. *Psychological Methods*, *11*, 344–362. https//doi.org/10.1037/1082-989X.11.4.344

Meagher, B. R., Leman, J. C., Bias, J. P., Latendresse, S. J., & Rowatt, W. C. (2015). Contrasting self-report and consensus ratings of intellectual humility and arrogance. *Journal of Research in Personality*, *58*, 35–45. https://doi.org/10.1016/j.jpr.2015.07.002

Park, B., Kraus, S., & Ryan, C. S. (1997). Longitudinal changes in consensus as a function of acquaintance and agreement in liking. *Journal of Personality and Social Psychology*, *72*, 604–616. https://doi.org/10.1037/0022-3514.72.3.604

Paulhus, D. L., & Reynolds, S. (1995). Enhancing target variance in personality impressions: Highlighting the person in person perception. *Journal of Personality and Social Psychology*, *69*, 1233–1242. https://doi.org/10.1037/0022-3514.69.6.1233

Rau, R., Carlson, E. N., Back, M. D., Barranti, M., Gebauer, J. E., Human, L. J., Leising, D., & Nestler, S. (2020). What is the structure of perceiver effects? On the importance of global positivity and trait-specificity across personality domains and judgment contexts. *Journal of Personality and Social Psychology*. https://doi.org/10.1037/pspp0000278

Romney, A. K., Weller, S. C., & Batchelder, W. H. (1986). Culture as consensus: A theory of culture and informant accuracy. *American Anthropologist*, *88*, 313–338. https://doi.org/10.1525/aa.1986.88.2.02100020

Schlegel, K., Boone, R. T., & Hall, J. A. (2017). Individual differences in interpersonal accuracy: A multi-level meta-analysis to assess whether judging other people is one skill or many. *Journal of Nonverbal Behavior*, *41*, 103–137. https://doi.10.1007/s10919-017-0249-0

Srivastava, S., Guglielmo, S., & Beer, J. S. (2010). Perceiving others' personalities: Examining the dimensionality, assumed similarity to the self, and stability of perceiver effects. *Journal of Personality and Social Psychology*, *98*, 520–534. https://doi.org/10.1037/a0017057

Wallace, J. D., & Biesanz, J. C. (2020). Examining the consistency of the good target across contexts and domains of personality. *Journal of Personality*, *89*, 188–202. https;//doi.org/10.1111/jopy.12574

Wessels, N. W., Zimmermann, J., Biesanz, J. C., & Leising, D. (2020). Differential associations of knowing and liking with accuracy and positivity bias in person perception. *Journal of Personality and Social Psychology*, *118*, 149–171. https://doi.org/10.1037/pspp0000218

Appendix

Here, we consider three technical issues: the estimation of SRM variances for the half-block design, issues in the estimation of the eSRM elements by simple slope for each perceiver and target, and challenges in the estimation of the formal model.

Estimation of the SRM Variances for the Half-Block Design

If there are no missing data in the half-block design, the estimates of the standard SRM variances of $\sigma_p{}^2$, $\sigma_t{}^2$, and $\sigma_r{}^2$ can be obtained from a two-way, perceiver by target, random effects Analysis of Variance (ANOVA). The estimate of perceiver variance, $s_p{}^2$, is given by $(MS_P - MS_{PxT})/n_t$, the estimate of target variance, $s_t{}^2$, is given by $(MS_T - MS_{PxT})/n_p$, and the estimate of perceiver by target or relationship variance, $s_r{}^2$, is given by MS_{PxT}. Estimation is also possible using multilevel modeling (Hehman et al., 2017), which has the advantage over the ANOVA approach of being able to handle missing data. However, if there are no missing data, the multilevel estimates and ANOVA are essentially the same, assuming all components are non-zero.

Estimation of the eSRM by Regression

We have proposed a straightforward method of estimate the eSRM elements: the regression approach, which is illustrated in Figure 1. Although this method of estimation is intuitive and straightforward, there are three drawbacks to this approach. First, using Dissimilation as an example, because the perceiver's data are used in computing the target means, the coefficient is inflated and the error variance is under-estimated because the same data are used as both predictor and outcome. Second, the predictors in the regression equation should be the actual perceiver and target effects, rather than the estimated perceiver and target effects. Using the estimated, not actual, effects result in the estimated slope being attenuated due to unreliability in the predictor. Third, the formal eSRM allows correlation between the perceiver effect or p and the perceiver's Sensitivity or c and between the target effect or t and the target's Prototypicality or a. The presence of these correlations requires that the c and a slopes should be simultaneously estimated.

Following up on the third point, consider the simple regression estimates of a for each target. For the simple slope to be an unbiased estimator of a, the correlation between the perceiver effect or p and the perceiver's Sensitivity or c must be zero. If that correlation were non-zero, the simple slope estimates $a_j + t_j b_{cp}$, where b_{cp} is the regression of c slope on the perceiver effect. The issue then becomes how to subtract from the slope estimate the term $t_j b_{cp}$ to obtain an estimate of a_i. We adopted the following

Table A1. eSRM Estimates for the Example Dataset in Table 1.

Perceiver	c	Differentiation	Dissimilation	Target	a	a'	Volatility	Dissensus
Ann	0.641	0.790	1.169	Alex	0.590	0.615	1.737	1.365
Barb	1.235	2.045	2.264	Bob	0.760	0.776	0.961	1.344
Cat	1.165	1.377	1.886	Carl	1.630	1.638	1.554	2.832
Dot	0.653	1.789	2.237	Dave	0.580	0.547	1.708	1.903
Eve	1.306	1.923	2.112	Ed	1.440	1.424	2.081	2.587

Note. Differentiation is the standard deviation of relationship effects and related to the d parameter in the formal model; Volatility is the standard deviation or relationship effects and related to the v parameter; the parameters c and a are simple slopes and c is the estimate of Sensitivity and a' is the adjusted slope and the estimate of Prototypicality.

strategy: We fixed the correlation between t and a to be zero. Given this zero correlation, the simple slope estimates of the c's are unbiased. We can then compute b_{cp} and with that value, we can adjust the simple slope estimates of a by subtracting $t_j b_{cp}$. In computing the standard deviation of the residuals, we adjust the standard deviation to improve the estimates: For Differentiation, we multiply that standard deviation of the residuals by the square root of $(n_t - 1)(n_p/[(n_p - 2)(n_t - 2)])$, and for Volatility, we multiply that standard deviation or the residuals by the square root of $(n_p - 1)(n_t/[(n_p - 2)(n_t - 2)])$.

As an illustration,[7] for the data in Table 1, Table A1 gives Alex's simple slope estimate of a as 0.590. The estimate of b_{cp} is 0.016 and the target effect for Alex is -1.500. The result then for Alex's adjusted a, denoted as a' in Table A1, is $0.590 - (0.016)(-1.500) = 0.615$. In the same way, we can adjust the other a values, which are shown in Table A1. The table also included the standard deviation of relationship effects for perceivers and targets.

Challenges in the Estimation of the Formal Model

The eSRM has two major differences from the original SRM. They are differential slopes for perceiver and target effects and heterogeneity of variance parameters for perceivers and targets. Modeling each of these additions is challenging, and the combination of the two is extremely daunting.

The differential slopes for perceiver and target effects could be estimated by factor analysis. The regular SRM is a single-factor model, with perceivers as units and targets as variables, which makes the perceiver effect the latent variable, and the target effects the variable intercepts. Note that in the standard SRM, the factor loadings are all fixed to one and the error variances are all set equal. Normally in factor analysis, we treat the variable intercepts as fixed, but they are random in the SRM. Several authors (e.g., González et al., 2008; Maydeu-Olivares & Coffman, 2006) have examined random intercepts in a factor analysis model and presumably, this approach could be applied to estimate a model with differential slopes. Note though that this approach would allow for variance in c slopes, but not the a slopes.

Turning our attention to heterogeneity, in a series of papers, Donald Hedeker (e.g., Hedeker et al., 2009) has developed multilevel models in which error variances are heterogeneous. We have modeled our specification of differential error variance based on his approach. Moreover, Brunton-Smith et al. (2017) have estimated heterogeneous variances with two-way (e.g., perceiver by target) or cross-classified structures, which allows for the modeling of covariates as predictors of those variances.

To estimate the combined model of differential slopes and error variance is a difficult challenge. We know of no current program that could directly estimate the full eSRM. One possible estimation strategy would be Bayesian estimation and we encourage the investigation of such a possibility. We expect that eventually there would be a way to estimate the model's parameters and evaluate whether the posited individual differences postulated by the eSRM presented here are statistically justifiable.