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

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Abstract

The Social Relations Model (SRM) partitions social perceptions into perceiver, target, and relationship effects. The SRM presumes that variability in these effects is consistent across perceivers and targets—that there is the same level of variability in their perceiver, target, and relationship effects. We introduce the extended SRM to examine individual differences in each component of the SRM. To do so, we separate the tendency for perceivers to see targets in different ways, called *Dissimilation*, into two novel constructs, *Sensitivity* and *Differentiation*. Similarly, we separate the tendency for targets to be viewed in different ways, called *Dissensus*, into two novel constructs called *Prototypicality* and *Volatility*. In three studies, we show the utility of this separation for understanding how perceivers use rating scales, the accuracy of judgment, and the meaning of the perceiver effect. The new model is discussed in relation to Funder's Realistic Accuracy Model and Biesanz's Social Accuracy Model.

Keywords: interpersonal perception, consensus, assimilation, accuracy

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In 1965, Dornbusch et al. posed a fundamental question for social and personality psychologists: Does a perceiver's judgment of a target reveal more about the perceiver or the target? Different groups of researchers (e.g., Hehman et al., 2017; Kenny et al., 1994; Malloy et al., 1995; Norman & Goldberg, 1966) have suggested using variances to answer this question, and currently the most commonly employed method to do so is the Social Relations Model (SRM; Kenny & La Voie, 1984). The SRM decomposes social perceptions into three primary elements:

- 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, and
- 3) the relationship effect or the tendency for a perceiver to view a particular target in a certain way.

As explained below, variance due to the perceiver effect can be used to assess assimilation, which reveals information about perceivers. Similarly, variance due to the target effect to assesses consensus, which reveals information about targets. Additionally, Malloy and Albright (1990) have suggested that variance in the relationship effect taps what they call *uniqueness* in social perception.

As an example, 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

Art 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).

The SRM quantifies these perceiver, target, and relationship effects. The formal model (see Kenny, 2020) states for perceiver i 's judgment of target j

$$X_{ij} = m + p_i + t_j + r_{ij} \quad (1)$$

Where m is a constant term, p is called the perceiver effect, t the target effect, and r the relationship effect.¹ In the SRM, the variables p , t and r , are random variables whose variances are σ_p^2 , σ_t^2 , and σ_r^2 , respectively. (See Appendix for how these are estimated.) For the data in Table 1, the perceiver variance is 2.025 and would be large when perceivers' mean ratings of targets vary considerably from one perceiver to the next. Because it represents the tendency for a perceiver to see targets in the same way, it represents assimilation. Additionally, the target variance is 1.650 and would be large when mean ratings of targets vary from one target to the next. Because it represents the tendency for targets to be viewed in the same way, it represents consensus or agreement about persons. Finally, there is relationship variance, which equals 2.375, which has been called *uniqueness*.

Estimates of assimilation, consensus, and uniqueness can alternatively, and more commonly, be represented as the *relative* variance of a given component. Assimilation is typically measured by the proportion of perceiver variance or $s_p^2/[s_p^2 + s_t^2 + s_r^2]$, consensus is measured by the proportion of target variance or $s_t^2/[s_p^2 + s_t^2 + s_r^2]$, and uniqueness is measured by $s_r^2/[s_p^2 + s_t^2 + s_r^2]$. With these proportional measures, assimilation, consensus, and uniqueness are defined as the amount of variance for a given component relative to the total variance. For the data in Table 1, the relative variances are .335, .273, and .393, respectively.

Inherent in this conceptualization of assimilation, consensus, and uniqueness is a nomothetic perspective of social perception: All people and dyads are equally affected by perceiver, target, and relationship effects. For instance, the assumption is that all perceivers equally access the target effect. Thus, if judgments for each perceiver were plotted against the target effect, the slopes would all be equal, after allowing for differences in sampling error. Consider the five judgments of the two perceivers, Ann and Barb whose judgments are in Table 1. In Figure 1a, we have plotted their five judgments against the estimates of the target effects. Contrary to the assumption of the SRM, we see that the slope is much steeper for Barb (1.24) than it is for Ann (0.64). For Barb, targets judged as honest by other perceivers are viewed as particularly honest, whereas for Ann the average ratings by others has less of an effect. Figure 1a also shows deviations from the slopes in Barb and Ann's judgments. These deviations represent relationship effects, because they emerge when a perceiver's rating deviates from the target effect. Note that the relationship standard deviation for Barb's five judgments is larger (1.54) than Ann's relationship standard deviation (0.33). Barb has more idiosyncratic perceptions than does Ann.

In Figure 1b, we have also plotted the five judgments for targets Art and Carl as a function of the perceiver effects. We see that the slope is steeper for Carl (1.63) than for Art (0.59), meaning that people use their perceiver effect more—their default value for their typical views of others—in judging Carl relative to judging Art. Moreover, we see that the relationship standard deviations for Carl (1.23) and Art (1.18) are similar. These differences in slopes and deviations from slopes (i.e. relationship effects) for perceivers and targets suggest that the assumption of equal weight in the perceiver, target, and relationship effects in the SRM is violated. The goal of this paper is to extend the SRM to allow for individual differences in the

use of target, perceiver, and relationship effects and to explain their theoretical importance. In particular, we focus on Funder's (1995) concept of the "Good Judge" and "Good Target."

In building the extended Social Relations Model or eSRM, we assume that all perceivers judge the same targets and all targets are judged by the same perceiver, as in Table 1. Such a design has been called a half-block design (Kenny & La Voie, 1984). To aid in the understanding of this new model, we compute within-person standard deviation for each perceiver's judgments, and we call this standard deviation *Dissimilation* because it measures the absence of assimilation, and we denote it as $s_{p(i)}$ for each perceiver i . We also compute within-person standard deviation in the judgments received by each target, denoted as $s_{t(j)}$ for each target j , which is called *Dissensus* after Jung (1999).

Conceptually, each perceiver's level of Dissimilation could emerge for two distinct reasons. First, a given perceiver profile of judgment might closely match the judgments of other perceivers. We saw this in Figure 1a where Barb's judgments strongly mirrored the target effect more than Ann's. We refer to this phenomenon as *Perceiver Sensitivity*. Sensitivity likely sheds light on accuracy because it captures a perceiver's implicit knowledge of how other perceivers judge the targets. Second, 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 1b where the spread in Barb's errors was greater than Ann's. We refer to this element as *Perceiver Differentiation*. Differentiation likely indexes inaccuracy because it reflects deviations from the target effects, or average ratings received across perceivers. Taken together, Dissimilation can be conceptualized as due to variation in target and relationship variance across perceivers, the former being called *Perceiver Sensitivity* and the latter *Perceiver Differentiation*, each with its own implications for accuracy.

For Dissensus, a parallel analysis can be made. 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 Carl than of Art. In this example, Dot sees others as more honest than does Ann. In judging Carl, both Dot and Ann default to their standard views of others and conclude that Carl is honest and dishonest, respectively. However, in judging Art, Dot and Ann do not use their perceiver effects so much. That is, the perceiver effect was stronger for some targets—as was the case for Carl—and weaker for others—as was the case for Art. Because this implies that some targets are seen according to a perceiver’s general perception of others, we refer to this phenomenon as *Target Prototypicality*.

Second, a target might be seen very differently 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 Art and Carl had similar relationship variances. However, the relationship variance for Art and Carl are much larger than that for Ed, meaning that judgments of Ed depend more on idiosyncratic judgments made by targets rather than consensual judgments. 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 different levels of random error in the judgments received. Accordingly, Dissensus can be conceptualized as due to variation in perceiver and relationship variances across perceivers, the former being called *Prototypicality* and the latter *Volatility*.

Table 2 summarizes the definitions of the four elements of disagreement. No doubt, these new terms can be difficult initially to comprehend. We hope that by the end of the paper, the reader will have realized the benefits of making these distinctions.

The Extended Social Relations Model (eSRM)

We can expand the SRM to allow for individual differences in the use of perceiver, target, and relationship effects in a new model that we call the extended SRM or eSRM. The formal model is as follows:

$$X_{ij} = m + q_j p_i + k_i t_j + r_{ij} \quad (2)$$

where q and k are new parameters, whose means are equal to one and variances may be non-zero. The q term is a slope parameter, illustrated in Figure 1b, and captures Prototypicality; values of q_j greater than one indicate that judgments of target i depend on the perceiver effect more than other targets. The k term is a slope parameter, illustrated in Figure 1a, and captures Sensitivity. Values of k_i greater than one indicate that perceiver i uses the target effect more than other perceivers. The relationship variance for perceiver i judging target j or r_{ij} is assumed to equal:

$$\ln[\sigma_{r(ij)}^2] = z + g_i + h_j \quad (3)$$

where g and h have means of zero and a non-zero variance and $\ln$ is the natural logarithm function (Hedeker et al. 2009). Note that when g_i and h_j are zero, the relationship variance equals a constant of e^z , which is essentially the “average” variance, similar to σ_r^2 defined earlier. The g term captures Differentiation and the h term Volatility. For instance, if perceiver i 's value of g_i were greater than zero, that perceiver would have a greater level of relationship variance than other perceivers. The parameter g is illustrated by how far the points are from the lines in Figure 1a and parameter h is similarly illustrated in Figure 1b.

Estimation of these eSRM parameters is quite challenging and is in development, the details of which are discussed in the Appendix. For this paper, we use the regression approach that was illustrated earlier in Figure 1. Considering first Dissimilation, the judgments of perceiver i are predicted by using the target means from all perceivers. The equation for perceiver i 's judgment of target j or Y_{ij} is

$$Y_{ij} = a_i + b_i T_j + F_{ij} \quad (4)$$

where T_j is defined at 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 k_i , the Sensitivity of perceiver i and the standard deviation of the errors $S_{F(i)}$, an estimate of $e^{(z+g_i)/2}$, the Differentiation for each perceiver. It can be shown that a weighted average of the slopes squared and the error variance equals Dissimilation squared. We also note that the mean of the slopes necessarily equals one.

There is a parallel analysis for Dissensus. The simple equation for Y_{ij} , where i is the perceiver and j is the target, is

$$Y_{ij} = a_i + b_j P_i + F_{ij} \quad (5)$$

where P_i is defined at the mean rating given by perceiver i minus the grand mean of all ratings given and this equation is 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 q_j , Prototypicality for target j , as well as the standard deviation of the errors $S_{F(j)}$, a measure of $e^{(z+h_j)/2}$, the Volatility for each target. It can be shown that a weighted average of the slopes squared and the error variance equals Dissensus squared. We also note that the mean of the slopes necessarily equals one.

There are drawbacks to the regression estimation strategy, which are reviewed in the Appendix. They center on the fact that the method uses estimates of the perceiver and target effect, not the true effect. Eventually, a better, though almost certainly more complex estimation method will be developed. Our purpose here is to show how using intuitively simple estimates (i.e., slopes and the standard deviation of errors) paves the way for the eSRM to advance our understanding of individual differences in social perception.

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. All three studies presented in this paper use a replication design. Additionally, to reduce some of the estimation problems described in the Appendix for the regression approach, it is beneficial to have a relatively large number of both perceivers and targets, a point also strongly emphasized by Judd et al. (2017).

What Might we Learn from the eSRM?

The eSRM introduces a new way of thinking about social perception that has implications for individual differences in each element of the original SRM.

First, the eSRM sheds light on the source of variability in each SRM component. Why, for example, do perceivers see targets as different from one another? According to the eSRM, the answer could be Sensitivity, as a perceiver differentiate targets in a way that closely matches how the targets are generally viewed. Alternatively, the answer could be Differentiation, as a perceiver could judge targets as very different from one another in way that is unique to that perceiver. Because Dissimilation is the combined effect of a perceiver's Sensitivity and Differentiation,² we can regress Dissimilation on the eSRM estimates for Sensitivity and

Differentiation to obtain standardized beta weights to assess the relative importance of Sensitivity and Differentiation in determining Dissimilation. A similar analysis can be conducted to determine the relative importance of Prototypicality and Volatility in predicting Dissensus.

Moreover, these beta weights can be correlated with their relative SRM variances across traits. We might expect that if a trait has more target variance (i.e. there is considerable consensus about the honesty of a set of targets), then Sensitivity would matter more than Differentiation. Alternatively, if a trait has more relationship variance, then Differentiation would matter more than Sensitivity. Similarly, the betas for Prototypicality might correlate with relative perceiver variance whereas the betas for Volatility correlate with the relative perceiver relationship variance.

Dissimilation

The eSRM partitions Dissimilation into Sensitivity and Differentiation. Conceptually, these two elements can be combined into two different effects, spread and accuracy. We first consider spread.

Dissimilation at the aggregate level, i.e. Sensitivity plus Differentiation, offers possible insight into a spread effect. At the extreme, a perceiver who sees all targets as identical, i.e., zero Dissimilation, would have the lowest possible value of Dissimilation. To see this, imagine a perceiver in Figure 1a with a slope of zero and no deviations: Regardless of how honest other perceivers view a target, the perceiver judges all the targets in the same way. Perceivers scoring high on Dissimilation would use a wide range of numbers, whereas those low on Dissimilation would use a narrower range. Perceiver differences in spread have been long known in the social-judgment literature (e.g., Wyer, 1969), but have been largely ignored. Moreover, the presence of spread differences complicates the comparison of variance differences between

groups of perceivers. For instance, if an SRM study were conducted comparing two groups of perceivers (e.g., Europeans and Africans), it might be the case that the SRM variances differ due to spread: one group showing greater SRM perceiver, target, and relationship variances than the other group. Finding more variance for that group does not reflect anything substantively interesting, but is due to group differences in scale usage.

One way to determine if there is a spread effect is to compute the correlation between Sensitivity and Differentiation across perceivers. If the correlation were positive, then a spread effect would be indicated.

Another possibility for Dissimilation is that the constituent parts of Dissimilation together reflect accuracy. As suggested by Funder (1995), there is the “Good Judge” and the “Poor Judge.” A good judge would have both a large value for Sensitivity, because it reflects agreement with other judges, as well as a low value for Differentiation, because it reflects deviations from those consensual judgments. There are several rationales for believing that a perceiver who agrees more with other perceivers is more accurate. First, as Funder (1995) has argued, agreement among perceivers could be used as a measure of accuracy because it is a necessary condition for accuracy; if perceivers are accurate that a target is honest, they must agree to some extent that the target is honest. Moreover, Kenny (2020) reviewed several studies showing that the target effect is the one SRM component that reflects accurate social judgment, correlating about .32 with the truth for first impressions and .60 when the perceivers are well acquainted with the target. 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. The formula, detailed in the Appendix combines Sensitivity and Differentiation such that accuracy increases as Sensitivity increases and

Differentiation decreases. If Dissimilation is driven by accuracy, there should be a negative correlation between Sensitivity and Differentiation.

We can also ask how trait-like each element is. Are individuals high in Sensitivity for judgments of Intelligence also high in Sensitivity for judgments of Honesty? Are those low in Differentiation always lower in Differentiation? For studies with multiple traits (e.g., Honesty, Attractiveness, Likeability), we can measure the correlation of Sensitivity and Differentiation across multiple traits. Each trait would serve as an item in a test and an internal-consistency reliability would be computed. For instance, finding that Sensitivity was reliably measured across traits would imply that a perceiver who agrees more with other perceivers on one trait also agrees with other perceivers on the other traits.

Correlations of Dissimilation (i.e., spread) and Accuracy with individual difference variables can help us elaborate each of their meanings. For instance, we might expect that women perceivers would have a higher level of Accuracy than do men (Hall, 1978). Additionally, we might measure the average self-rating with negative traits reversed to produce a measure of self-enhancement and correlate it with Accuracy, with the expectation that positive self-ratings would be negatively correlated with Accuracy in that inaccurate self-perceptions might be associated with inaccurate perceptions of others. For spread effects, it might be the case that mathematics aptitude might be correlated with Dissimilation because a person higher in mathematics aptitude might use a wider range of the scale than those lower in aptitude. Moreover, we might correlate the perceiver effect, both absolute and relative, with Dissimilation and Accuracy to evaluate if people who see others positively or more extremely have higher or lower levels of the two. We might expect that perceivers who generally see others more extremely would show larger spread effects.

Dissensus

Differences in how a target is judged by perceivers is due to perceivers using their perceiver effect more (i.e., Prototypicality) and due to idiosyncratic perceptions of that target (i.e., Volatility). Target differences in Prototypicality may due to differences between targets on the extent to which perceivers are familiar with them. The presumption would be that targets who are more familiar would show weaker Prototypicality, because prior research indicates that familiarity decreases the use of the perceiver effect (Kenny, 2020). The relation between likeability and Prototypicality is less clear. Because liking and familiarity are positively correlated, we might suspect lower levels of Prototypicality. Alternatively, because positivity (i.e., either seeing all targets positively or negatively) is the dominant component of the perceiver effect (Rau et al., 2020; Srivastava et al., 2010), it might be that likeable targets would show higher levels of Prototypicality.

In the same way that Funder (1995) suggested the notion of a “Good Judge,” he outlined the meaning of a “Good Target” and the eSRM components offer potential insights into this construct. Being a “Good Target” (Funder, 1995) would seem to imply a low level of Volatility: perceivers generally see a target the same way would suggest that that target is easier to judge. Human and Biesanz (2013) found that more socially adjusted persons were good targets. It would seem to be the case for strangers that those targets who exhibited strong cues (e.g., smiled a great deal and were physically attractive) would have lower levels of Volatility.

The direction of the correlation between the two elements of Dissensus is uncertain. Funder’s (1995) “Good Target” would have low Volatility, but theoretically, it is unclear whether they would have high or low Prototypicality. However, because empirically there is evidence that targets who resemble the typical other are more accurately judged (Human &

Biesanz, 2013) and because the perceiver effect is a measure of the perceiver's typical other, it seems plausible that targets who have higher levels of Prototypicality would have lower levels of Volatility.

As suggested above, we can measure the correlation of Prototypicality, as well Volatility, across multiple traits to determine how trait-like these elements are. As reviewed in Kenny (2020), evidence for the consistency of the good target is mixed, but several different studies do support that view. As such, Prototypically might correlate positively across traits, with targets that more agreement about a particular target on one trait is associated with more agreement on another trait. The dominant component of the perceiver effect is 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, Prototypicality is due to trait-specific effects, we would expect not to find consistency.

Relation to 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, usually operationalized as the targets' self-rating, 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 target's self-ratings (conceptualized as 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 the SAM, the eSRM allows for individual differences in sensitivity to the truth, but

SAM typically operationalizes truth as self-ratings whereas the eSRM operationalizes truth as consensual judgments.

Another major difference is that SAM simultaneously examines relationships across many traits, i.e., multivariate, whereas the eSRM examines one trait at a time, i.e., univariate. 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 error (i.e., relationship) variances, accuracy can be greater if the slope is greater or the error variance is weaker.

Current Studies

We present the results from three different studies. The first two studies were part of Jung's 1999 dissertation on Dissensus. In the first study, the perceivers were well acquainted with the targets who were famous celebrities. The second of the Jung studies examined judgments by perceivers who viewed strangers interacting for four minutes. The third study is a re-analysis of a 1992 study in which the perceivers observed a target who was alone for 20 seconds.

By varying how acquainted perceivers are with the targets, we can see how the four elements operate differently at different levels of acquaintance. Presumably, at low acquaintance the perceiver effect is more important, which should lead to more variance in Prototypicality, whereas at high acquaintance, the target effect would be more important, which should lead to more variation in Sensitivity. Moreover, in the last two studies, perceivers have the same information about the target, whereas in Study 1 they potentially have different sources of information. Presumably, there should be greater levels of Volatility when perceivers have different information.

Because the data were gathered more than 20 years ago, the analyses were not preregistered. Given this lack of preregistration, the analyses should be treated as exploratory. The codebooks, data, and R Markdown analyses for all three studies can be downloaded at https://osf.io/j9x7h/?view_only=d06920a43a70446bb9836324abceec09. For all tests in all three studies, we used an alpha of .05. In measuring correlates of the four element with individual difference variables, we typically use the composite across the set of traits. We do so even when the indication of the reliability of the composite is low to diminish the possibility of capitalization on chance. After we present the results from the three different studies, we summarize the major conclusions.

Study 1: The Celebrities Study

Method

In this study, 160 participants provided judgments of 40 different targets on 20 different traits. The study was conducted 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 4 different sets of 10 and traits were divided into 2 different sets of 10. The perceivers were divided into 8 sets of 20, where each set consisted of one of the 4 sets of 10 targets and one of the 2 sets of 10 traits. The result was that

each target was 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. Perceivers also reported their gender and self-ratings of the 10 traits that they judged.

Analysis

For each trait, the analysis was conducted within each half block of 20 perceivers and 10 targets and then pooled across the 4 sets. Where necessary, analyses removed variance due to set.

Results and Discussion

A regular SRM partitioning of variance was conducted. On average, the percentage of perceiver variance was 14.1, target variance was 29.5, and relationship variance was 56.4. These results are comparable to a recent review of twelve long-term acquaintance studies (Kenny, 2020). All of the 20 traits had statistically significant ($p < .05$) perceiver and target variances that were greater than zero.

For each of the 20 traits, regression estimates of Perceiver Sensitivity and Differentiation for the 160 perceivers were used to predict Dissimilation, and for the 40 targets, Target Prototypicality and Volatility estimates were used to predict Dissensus. Standardized regression coefficients, betas, were used. Generally, the relationship elements, Differentiation and Volatility, had stronger beta weight than individual elements, Sensitivity and Prototypicality. For 7 of the 20 traits, Sensitivity was more important than Differentiation, but for none of the 20 traits was Prototypicality more important than Volatility.

We correlated these betas with the relative SRM variances using trait as the unit. The level of relative target variance strongly correlated with the importance of Sensitivity ($r = .822$), the

level of relative perceiver variance moderately correlated with the importance of Prototypicality ($r = .451$), the level of relationship variance strongly correlated with the importance of Differentiation ($r = .924$), and the level of relative relationship variance correlated moderately with the importance of Volatility ($r = .480$). The two Dissimilation elements of Sensitivity and Differentiation closely mirrored their relevant SRM component whereas the Dissensus elements of Prototypicality and Volatility were less strongly associated.

To determine how “trait-like” each element is, we measured the correlation of each element across the pairs of traits. We first examined whether the consistency was greater between two indicators of the same Big Five factor (e.g., both Warm and Cheerful, indicators of Agreeableness) than between two indicators of two different Big Five factors (e.g. Talkative, an indicator of Extraversion, and Warm, an indicator of Agreeableness). Across the four elements, there is stronger correlation between two indicators of the same Big Five factor (Mean $r = .199$) than between two traits measuring different Big Five factors ($M_r = .162$). The average inter-trait correlation between two indicators of the same Big Five factor was .202 for Sensitivity, .340 for Differentiation, .104 for Prototypicality, and .149 for Volatility, whereas the average inter-trait correlation between two indicators of different Big Five factors was .166 for Sensitivity, .192 for Differentiation, .084 for Prototypicality, and .205 for Volatility.

Because the correlations were usually larger within a Big Five factor than between, we used the average between-indicator correlation to compute an alpha for the sum of standardized scores.³ We obtained alphas of .666 for Sensitivity, .704 for Differentiation, .477 for Prototypicality, and .721 for Volatility. Notice that the two relational elements of Differentiation and Volatility demonstrate higher levels of internal consistency than Sensitivity and Prototypicality. The levels of reliability for Differentiation and Volatility are acceptable, for

Sensitivity, poor, and the alpha for Prototypicality, unacceptable. Nonetheless, subsequent correlational analyses use the sum score across traits and not the individual traits to reduce the number of correlations.

For each trait across perceivers, we correlated the level of Sensitivity with Differentiation. Across the 20 traits, the average correlation across the 20 traits between Sensitivity and Differentiation was .209. We summed Sensitivity and Differentiation across the rated traits and correlated them and the correlation was .530 ($p < .001$). Earlier, we noted that there were factors that might make the Sensitivity-Differentiation correlation positive (i.e., spread) and other factors that might it negative (i.e., accuracy). The strong positive correlation between Sensitivity and Differentiation provides support for the spread hypothesis.

Across targets, we correlated the levels of Prototypicality and Volatility and the average correlation across the 20 traits between Prototypicality with Volatility was .111, and the correlation of summed Prototypicality and Volatility was .153 ($p = .367$). It appears that Prototypicality and Volatility are relatively independent in this study.

We next examined external correlates with each of the measures. We first examined correlations between perceiver self-ratings with both Dissimilation and Accuracy. The average correlation between self-ratings across the 20 traits with Dissimilation (i.e., spread) was .041 and with Accuracy was .013. Self-ratings were averaged across the ten traits rated by each perceiver, reversing the negative traits, and extremity was measured by computing the sum of the absolute value of the score minus the mean across perceivers. A multiple regression was used to examine the effects of Average Self-Rating and Average Extremity on Dissimilation and Accuracy. For Accuracy, there were no effects, but for Dissimilation, Average Self-Rating had a marginally significant positive effect ($\beta = 0.253, p = .063$) and Extreme Self-Rating had a significant

positive effect ($\beta = 0.362, p < .001$). We suspect that the effect of Self-Rating Extremity is further evidence of a spread effect in that an extreme self-rating is an indication of using a greater range of the scale.

We also correlated gender of the perceiver (coded as 0 for men and 1 for women) with Dissimilation and Accuracy. The correlation with Accuracy was .134 ($p = .099$), a weak correlation, but consistent with the often-reported finding that women are more accurate than men. There was little or no relationship of Dissimilation with gender ($r = .065, p = .422$).

We next examined Familiarity and Liking for each perceiver and each target. To predict Sensitivity and Differentiation, we used the perceiver effects of Familiarity and Liking – the tendency of the perceiver to say that he or she is generally familiar with the targets and the tendency to say they like all the targets. To predict Prototypicality and Volatility, we 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. The reliability of the estimates of the perceiver effect was .821 for Familiarity and .643 for Liking and of the target effect was .844 for Familiarity and .941 for Liking. We found a .498 correlation between these two perceiver effects and a .350 correlation between these two target effects. We conducted a multiple regression analysis to account for collinearity between Familiarity and Liking. Looking first at perceivers, we did not find any statistically significant effects of either Familiarity or Liking on Dissimilation and Accuracy. However for targets, there was a clear result for Volatility that Liking was a statistically significant negative predictor ($p < .001, \beta = -0.641$), but Familiarity had no effect ($p = .979, \beta = -0.003$). Thus, there was greater consensus for targets who are liked more. For Prototypicality, the effect of Familiarity ($\beta = 0.312$) was only marginally significant ($p = .073$), whereas the effect of Liking ($\beta = -0.114$) is absent ($p = .505$).

Finally, we have estimates of the perceiver and the target effects averaged across the traits. (We reversed negative traits before averaging across the traits.) We also measured perceiver and target extremity effects by computing the absolute value of the target effects and then averaging across the traits. We conducted multiple regression analyses with both Average Effect and Average Extremity as predictors. Looking first at perceivers, we did not find any statistically significant effects for Differentiation. For Accuracy, we did find a marginally significant result for Perceiver Extremity ($\beta = -0.152, p = .074$), which means that those with extreme perceiver effects on the traits were less accurate. For targets and Prototypicality, there were no significant effects. However for Volatility, we found that the effect of Extremity was strongly positive ($\beta = 0.573, p < .001$), and the Average Effect had a marginally significant negative effect ($\beta = -0.244, p = .056$). Taken together, these effects imply that more extreme targets are more difficult to judge, especially when they were viewed negatively, whereas targets seen more positively were easier to judge.

Study 2: The Brief Acquaintance Study

Study 1 used targets that were familiar to the perceivers. We might expect that Dissimilation and Dissensus would be very different when perceivers first become acquainted with the targets. In this second study, perceivers observed a stranger target interacting with another person for four minutes.

Method

Jung (1999) obtained the 40 videotapes used in Study 2 of Funder et al. (1995). In that study, 40 mixed-gendered stranger dyads interacted for 5 minutes. They were instructed “to talk about whatever they like.” Jung discarded 8 tapes for data quality reasons and used 4 minutes of the 5-minute tape. From each tape, he chose one of the two members on the tape as the target, 16

men and 16 women. The 32 targets were divided into 4 different sets of 8 and were judged by 20 perceivers on all 20 different traits. The result was that each target was judged on each trait by 20 different perceivers, and for each trait, 80 perceivers made judgments. The same 20 traits that were used in Study 1 were used in this study. There are no individual difference variables currently available for this study.

Analysis

For each trait, the analysis was conducted within each half block of 20 perceivers and 8 targets and then pooled across the 4 sets. Where necessary, analyses removed any variance due to set.

Results and Discussion

A regular SRM partitioning of variance was conducted. On average, the percentage of perceiver variance was 19.7, target variance was 22.2, and relationship variance was 58.1. All of the 20 traits showed statistically significant perceiver and target variances. Finding less target variance and more perceiver variance from that found in Study 1 is to be expected because the perceivers were much less familiar with the targets. Likely, less of the “relationship” variance is true relationship variance than for Study 1 in that in this study, all perceivers had exactly the same information about the target.

For each of the 20 traits, estimates of Sensitivity and Differentiation for 80 perceivers were used to predict Dissimilation and estimates of Prototypicality and Volatility for 32 targets were used to predict Dissensus. Standardized regression coefficients, betas, were used to measure importance. As with Study 1, the relationship elements, Differentiation and Volatility, were more important than the individual elements, Sensitivity and Prototypicality. However, for 8 of the 20

traits, Sensitivity was more important than Differentiation, and for 3 of the 20 traits, Prototypicality was more important than Volatility.

We also correlated these betas with the relative SRM variances for each trait. The level of the relative target variance strongly correlated with the importance of Sensitivity ($r = .798$), the level of the relative perceiver variance was not statistically correlated with the importance of Prototypicality ($r = .102$), the level of relative relationship variance was correlated with the importance of Differentiation ($r = .686$) and Volatility ($r = .610$). With the exception of Prototypicality, each element mirrored its relevant SRM component, a result similar to that found in Study 1.

To determine how “trait-like” each element is, we measured the correlation of each element across the different pairs of traits. We first examined whether the consistency was greater between two indicators of the same Big Five factor (e.g., both Warm and Cheerful, indicators of Agreeableness) than between two indicators of two different Big Five factors (e.g. Talkative, an indicator of Extraversion and Warm, an indicator of Agreeableness). Across the four elements, there was a stronger correlation between two indicators of the same Big Five factor (Mean $r = .174$) than between two traits measuring different Big Five factors ($M = .129$). The average inter-trait correlation between two indicators of the same Big Five factor was .224 for Sensitivity, .216 for Differentiation, .074 for Prototypicality, and .183 for Volatility, whereas the average inter-trait correlation between two indicators of different Big Five factors was .119 for Sensitivity, .228 for Differentiation, .035 for Prototypicality, and .134 for Volatility. We computed the alpha of the sum of standardized scores using the average of only the between-indicator inter-trait correlations and the result was .729 for Sensitivity, .856 for Differentiation, .423 for Typicality, and .756 for Volatility. As in Study 1, the two relational

elements of Differentiation and Volatility demonstrate higher levels of internal consistency than Sensitivity and Prototypicality. The levels of reliability for all but Prototypicality are acceptable (a result also obtained in Study 1), but to reduce the number of analyses, we use the composite for all four elements.

For each trait across perceivers, we correlated the levels of Sensitivity with Differentiation, and across targets, we correlated the levels of Prototypicality with Volatility. Across the 20 traits, the average correlation between Sensitivity and Differentiation was .144, whereas the average correlation between Prototypicality with Volatility was .038. These results are comparable to the findings in Study 1. For perceivers, the correlation between the sum of Sensitivity and Differentiation was .471 ($p < .001$), which suggests an overall effect of spread. That is, some perceivers used a wide range of numbers and others a narrow range. For targets, the correlation was -.556 ($p = .002$), which is very large. We do note that in Study 1, the correlation was slightly positive, .153. Perhaps for first impressions, the two elements are involved in a compensatory process: If the target is highly prototypical, that target shows very low Volatility. The large negative correlation is even more impressive when we factor in the low reliability of the summed Prototypicality score.

Finally, the perceiver and the target effects were averaged across the traits and correlated with each element. (We reversed negative traits before averaging.) We also measured perceiver and target extremity effects by computing their absolute value of the perceiver and target effects and then averaging across the traits. We conducted multiple regression analyses with both Average Effect and Average Extremity as predictors. For perceivers, there was no effect of the Average Perceiver Effect, but there were effects of Average Extremity: Those perceivers with more extreme perceiver effects were less accurate ($\beta = -0.231$, $p = .050$) and showed marginally

significant weaker spread effects ($\beta = -0.185, p = .100$). For targets, Extremity of the Target Effect had a strong negative effect ($\beta = -0.6469, p < .001$) on Prototypicality, whereas as its effect on Volatility was positive ($\beta = 0.443, p = .009$). This strong negative effect of Extremity on Prototypicality and positive effect on Volatility were also found in Study 1. The Average Target Effect had essentially no effect on Prototypicality ($\beta = -0.187, p = .223$), but a negative effect on Volatility ($\beta = -0.395, p = .014$). As in Study 1, more extreme targets, especially negative ones, are more difficult to judge.

Study 3: Zero Acquaintance

The perceivers in Study 2 observed strangers in social interaction for four minutes. What would happen if the observations were much shorter in time? In Study 3, we examine perceptions made of a target, after only observing alone for a few seconds, which has been called *zero acquaintance* (Kenny, 2020).

Method

All perceivers and targets were undergraduates from the University of Connecticut in 1987. The targets were 64 undergraduate students who were secretly videotaped while waiting alone to interact with another person. The edited clips were approximately 20 seconds long. The 64 targets, who gave the original authors permission to use the clips, were divided into 2 different sets of 32, and one set was shown to 56 perceivers and the other to 57 perceivers. These targets were judged on 10 different bipolar traits, 2 each from the Big Five: Sociable-Reclusive, Irritable-Cheerful, Responsible-Irresponsible, Intelligent-Unintelligent, Unimaginative-Imaginative, Talkative-Silent, Calm-Anxious, Careful-Careless, Tense-Relaxed, and Cooperative-Negative. Note this is the Goldberg (1990) version of the Big Five, where Factor IV is Emotional Stability, not Neuroticism, and Factor V is Culture, not Openness. All ratings were on a 1 to 7 scale, where

the first pole (e.g., Sociable) was a “1” and the second (e.g., Reclusive) was a “7,” and scores that were negatively scaled (e.g., Sociable-Reclusive) were reversed so that larger numbers mean more positive ratings. There are individual difference measures for perceivers and targets, which are detailed later.

Analysis

For each trait, the analysis was conducted within each half block and the results were then pooled. All analyses controlled for set, i.e., the two groupings of the 32 targets.

Results and Discussion

We conducted a regular SRM partitioning of variance. On average across the 10 traits, the percentage of perceiver variance was 9.6, target variance was 14.7, and relationship variance was 75.7. All of the variances were statistically significantly greater than zero. Because the perceivers had only viewed the target for 20 seconds, it is unsurprising that the level of consensus was lower than that in the prior two studies. Because the targets are total strangers, the largest part, relationship variance, is likely error variance.

Using beta weights, we measured the relative weight of Sensitivity and Differentiation in determining Dissimilation and the relative weight of Prototypicality and Volatility in determining Dissensus. The relational elements, Differentiation and Volatility, were always the more important elements, a result most likely due to the greater levels of error variance in this study. We correlated these betas with the relative SRM variances using trait as the unit. The level of relative target variance strongly correlated with the importance of Sensitivity ($r = .754$), the level of relative perceiver variance weakly correlated with the importance of Prototypicality ($r = .228$), the level of relationship variance correlated with the importance of Differentiation ($r = .590$) and the relative importance of Volatility ($r = .713$). With the exception of Prototypicality,

each element mirrored its relevant SRM component closely. This pattern of correlations was essentially the same across the three studies.

To determine how “trait-like” each element is, we measured the correlation of each element across the different pairs of traits. We first examined whether the consistency was greater between two indicators of the same Big Five factor (e.g., both Sociable and Talkative, indicators of Extraversion) than between two indicators of two different Big Five factors (e.g. Talkative, an indicator of Extraversion and Cheerful, an indicator of Agreeableness). Across the four elements, there was a stronger correlation between two indicators of the same Big Five factor (Mean $r = .475$) than between two traits measuring different Big Five factors ($M_r = .257$). The average inter-trait correlation between two indicators of the same Big Five factor was .453 for Sensitivity, .755 for Differentiation, .301 for Prototypicality, and .391 for Volatility, whereas the average inter-trait correlation between two indicators of different Big Five factors was .246 for Sensitivity, .637 for Differentiation, .079 for Prototypicality, and .064 for Volatility. We computed the standardized alpha using the average of only the between-indicator inter-trait correlations and the result was .766 for Sensitivity, .946 for Differentiation, .462 for Typicality, and .407 for Volatility. As in the earlier two studies, the two relational elements of Differentiation and Volatility demonstrate higher levels of internal consistency than Sensitivity and Prototypicality. The levels of reliability for Differentiation and Volatility are acceptable, but the other two are unacceptable. The low level of consistency for Prototypicality replicated across all three studies.

For each trait across perceivers, we correlated the levels of Sensitivity with Differentiation, and across targets, we correlated the levels of Prototypicality with Volatility. Across the 10 traits, the average correlation between Sensitivity and Differentiation was .374, all 10 correlations

being positive, which is consistent with a spread effect: Some perceivers vary their ratings more than others, leading to perceivers who have greater Sensitivity also to have greater Differentiation, and those with lower Sensitivity also to have lower Differentiation. Perhaps, spread had a larger effect in this study due to the greater response burden of perceivers in this study (426 ratings for each perceiver) than in Study 1 (220 ratings) and Study 2 (160 ratings), as well as the difficulty of judging total strangers with minimal information. Another possibility is that spread effects might be stronger for bipolar versus unipolar rating. For targets, the average correlation across the 10 traits between Prototypicality with Volatility was $-.183$.

For perceivers, the correlation between summed Sensitivity and Differentiation was $.702$ ($p < .001$), which is very large. For targets, the correlation of summed Prototypicality and Volatility was $-.201$ ($p = .114$). A negative correlation was also found in Study 2. Both first-impression studies had a negative correlation between Prototypicality and Volatility.

Correlations for Perceivers. For perceivers, the individual difference measures are the gender, self-reported ratings of ability (Verbal and Math Scholastic Aptitude Test (SAT) score, grade point average (GPA), self-ratings of the traits, and estimated perceiver effects for the traits. Because of the large number of individual difference measures, the reader should be forewarned that capitalization on chance is probable. We focus on the overall pattern of results and caution the readers that our conclusions here are highly preliminary. There were small amounts of missing data for the demographic variables, self-reported measures of ability, and self-perceptions of the traits.

Considering first Accuracy correlations with Gender, SAT scores, and GPA, the only significant correlation ($p = .007$) was with Gender, equaling $r = .259$: Women were more accurate than were men. The two nontrivial correlations with Dissimilation were SAT Math ($r =$

.202, $p = .052$) and SAT Verbal ($r = -.251$, $p = .010$). Perhaps, people with strong verbal skills and those with weak mathematical skills used a smaller range of numbers than those with weak verbal skills and strong mathematical skills.

Perceivers with more positive self-ratings were slightly more accurate ($r = .099$), but not significantly so ($p = .308$). Positive self-ratings did not predict spread effects.

We next examined the effects of the perceiver effect estimates and perceiver extremity on Dissimilation and Accuracy. We measured perceiver extremity effects by computing the absolute value of the perceiver effects and then averaging across the traits. We conducted multiple regression analyses with both Average Perceiver Effect and Average Extremity as predictors. Looking first at Dissimilation, we find a positive statistically significant effect of the Average Effect ($\beta = 0.196$, $p = .036$), and a significant effect for Average Extremity ($\beta = 0.189$, $p = .043$). Thus, perceivers who see others more positively and more extremely use a wider range of the scale. For Accuracy, we found a positive statistically significant effect of the Target Effect ($\beta = 0.188$, $p = .049$), but no effects for Perceiver Extremity ($p = .606$). Perceivers who generally liked others showed a larger spread effect and were also more accurate.

Correlations for Targets. The analysis for targets is more difficult than it is for perceivers for several reasons. First, there are fewer targets (64) than there are perceivers (113). Second, there are about four times as many more individual difference variables for targets as there are for perceivers. Third, for perceivers, there are consistent individual differences across traits for both Sensitivity and Differentiation, whereas for targets, the reliability estimates for Prototypicality and Volatility were very low. We inspected the correlations for Prototypicality and Volatility with target self-ratings for the Big Five, average target effect estimates for the Big Five, average extremity scores for the target effect estimates for the Big Five, gender, two

self-reported trait measures (Social Desirability and Self-Monitoring), five observer judgments of appearance and behavior (Smiling, Formal Dress, Rapid Body Movements, Primping, and Attractiveness) that were found to predict judgments in the original study, and three self-reported ability measures (SAT Verbal and Math and GPA).

We first correlated self-ratings on the Big Five with both Prototypicality and Volatility. The only appreciable correlations were between self-ratings of Agreeableness with Volatility. Volatility correlated negatively with self-reported Agreeableness, i.e., people who see themselves as agreeable received lower levels of Volatility ($r = -.307, p = .015$). None of the correlations for Prototypicality was statistically significant.

We next examined the target effect estimates and target extremity on Prototypicality and Volatility. We conducted a multiple regression analysis with both the estimated Target Effect and Target Extremity as predictors. We found no effects for Prototypicality, but for Volatility, targets seen more positively had significantly lower levels ($\beta = -0.527, p < .001$). Unlike the prior two studies, the effect for extremity on Volatility was negative ($\beta = -0.263, p = .026$). In this study, very positive targets were judged with greater consensus.

Next, we examined the correlation of observers' ratings of the targets' behavior and appearance with Prototypicality and Volatility. Here we examined the Big Five factors computed using the traits that were found to correlate with the behavior and Attractiveness (see Table 5 in Kenny et al., 1992). Of the nine possible correlations, the only statistically significant correlation for Prototypicality was Attractiveness with Extroversion, $r = .430$ ($p < .001$), and the average of the other eight correlations was only .01. For Volatility, most of the correlations were negative, but only Smiling correlated significantly with Agreeableness ($r = -.286, p = .023$).

Women targets were lower on Volatility than men ($r = -.322, p = .010$). Neither the Social Desirability nor the Self-Monitoring scales yielded any statistically significant correlations. Finally, Math SAT and GPA did not yield any significant correlations. However, Verbal SAT did show a positive correlation with Prototypicality ($r = .264, p = .042$).

Summary and General Discussion

We have reported many results from three different studies. Here, we cautiously summarize and interpret those results, first for Dissimilation and then for Dissensus. For each, key questions are whether there is any benefit in separating the two different elements and the meaning of each of the elements.

Dissimilation

Sensitivity and Differentiation explain individual differences between perceivers in the degree to which they perceive targets as different from one another. Sensitivity measures the extent to which differences in a perceiver's judgment matches the target effect and can has implications for accuracy. Differentiation measures variation in a perceiver's judgments that is not explained by the target effect and has implications for inaccuracy. In this paper, we defined accuracy as the combination of Sensitivity and Differentiation (see the Appendix).

Differentiation explains more of the variance of Dissimilation than Sensitivity, in large part because in all three studies there is more relationship variance than target variance. Sensitivity is a stronger determinant of Dissimilation when there is more target variance (average r of .791), and Differentiation correlates with relationship variance (average r of .733). Thus, the presence of each of these components is closely tied to its relevant SRM component.

Sensitivity also shows a reasonable level of consistency across traits, with an average alpha of .720, and so does Differentiation, with an average alpha of .835. What, then, is the

meaning of individual differences in these two elements? Several sources of evidence point to differences in Dissimilation reflecting differences in spread: Some perceivers use the entire range of possible values, i.e., greater spread, leading to both greater Sensitivity and Differentiation, whereas other perceivers use a narrower range leading to lesser amounts of each element. The main source of evidence for spread underling Dissimilation is the positive correlation between Sensitivity and Differentiation. We do find positive correlations at the trait level, the average correlation across studies being .242, and stronger positive correlations when Sensitivity and Differentiation are averaged across traits, the correlation across the three studies being an impressive .677. The correlation is “weakest” equaling .530 in Study 1 where perceivers are well acquainted with the targets. We suspect that when the judgment task is more difficult, spread differences are more apparent. We also find some evidence in Study 3 that those scoring high on Verbal SAT and those scoring low on Math SAT use a narrower range of scores.

Besides spread, Sensitivity and Differentiation can be combined to form an Accuracy score or correlation of a perceiver’s judgments with the target effect. The eSRM Accuracy score is a way of operationalizing Funder’s (1995) “Good Judge.” We note that the correlation of Accuracy with Dissimilation averaged across the three studies is just .050. Thus, the two are essentially independent.

In Studies 1 and 3, we correlated gender with Accuracy and found correlations of .134 and .258, respectively. These certainly are not strong correlations, but they are consistent with the long-established finding that women perceivers are more accurate than men perceivers (Hall, 1978).

In all three studies, we examined the effects of seeing others favorably, measured by the average perceiver effect, larger numbers implying more positive perceptions, and extremity on

Dissimilation and Accuracy. Across all three studies for Accuracy, perceivers who see others more positively were more accurate and perceivers who see others more extremely were less accurate. The rationale for these two correlations is not obvious to us.

Self-measures were available for perceivers in Studies 1 and 3. Overall, there was no evidence of a correlation of these measures with either Dissimilation or Accuracy.

In sum, there is clear evidence for a spread effect. Our finding of spread differences may not be very surprising, but they have been largely ignored in the literature. As we discussed earlier, the presence of spread differences complicates the comparison of variance differences between groups of perceivers. To control for spread differences, it makes more sense to compare the group's relative and not absolute variances. Perhaps also, certain experimental instructions (e.g., "Try to use all the numbers in rating the targets.") might minimize the spread effect.

The eSRM and SAM measures of accuracy are different. The eSRM measures accuracy as a correlation and uses average judgment as the measure of truth, whereas SAM measures accuracy as a slope and has self-ratings as a measure of the truth. One advantage of the eSRM is that it allows perceivers to differ on the relationship variances, whereas SAM presumes homogeneity. It would be interesting to compare the two models' measures of perceiver accuracy. Likely, because both Sensitivity and SAM's perceiver accuracy are slopes, those two would correlate more highly than the eSRM Accuracy with SAM's perceiver accuracy. In fact, it would be interesting to know how much of the variation in perceiver accuracy, as defined by the SAM, is explained by Sensitivity.

Spread differences between perceivers might create difficulties in SAM in that greater spread in a perceiver's judgments would likely lead to weaker slopes. Perhaps there might be

some way to take eSRM estimates of perceivers' spreads and use them to adjust perceivers' judgments before conducting a SAM analysis.

Dissensus

Prototypicality and Volatility explain differences between perceivers in how they view a target. Prototypicality measures the extent to which perceivers' judgments of a given target matches their perceiver effects and Volatility measures variation in the judgments of a target not explained by the perceiver effect. We first consider Volatility and then Prototypicality.

Volatility taps the extent to which the target is either a "Good Target" or a target that is difficult to judge. Across three studies, we find consistency across traits in two studies, but in the zero-acquaintance study, its consistency is poor.

In the zero-acquaintance study, we found that women and people seen as agreeable had lower level of Volatility. In addition, Volatility for Agreeableness was lower for people who smiled. Perhaps "nice people" are judged with greater consensus. The presence of a diagnostic cue, e.g., smiling, resulted in lower Volatility. This result can be interpreted in terms of Funder's (1995) Realistic Accuracy Model, in that cues are diagnostic, a process Funder calls *availability*, are necessary for there to be accuracy.

The relation of Average Target Effect and Volatility was consistently negative in all three studies. Also in Study 1, where there is a measure of Liking, targets who are liked show lower levels of Volatility. Evidently, people who are liked are easier to judge. The result is perhaps consistent of the finding of Human and Biesanz (2013) that more adjusted persons are "good targets." However, the effect of the Average Target Extremity on Volatility is less consistent. In the first two studies, its effect is positive, whereas in Study 3, its effect is negative, with all three effects being statistically significant. Perhaps it is the case that when there is minimal

information, but that information is positive (e.g., the target is smiling), there is greater consensus.

As we discussed earlier, Biesanz's SAM measures the extent to which targets are accurately judged, which is called *distinctive target accuracy* in SAM. Perhaps Volatility is inversely related to that construct, in that Volatility measures disagreement and distinctive target accuracy measures agreement. It would be interesting to see if Volatility and distinctive target accuracy are negatively correlated.

The results for Prototypicality are disappointing. We find across all three studies a very low level of consistency across traits, their average being just .454, which is by far the lowest of the four elements. This low consistency suggests that Prototypicality is not due to the positivity part of the perceiver effect (i.e., the general tendency to like or dislike all targets) because positivity affects all traits. Rather, the likely source of Prototypicality is variance in trait-specific effects of the perceiver effect (Rau et al, 2020; Srivastava et al., 2010). For instance, Ann sees others as very Cheerful and Boring. For Bob who is very prototypical, Ann would see him as very Cheerful and very Boring whereas for Carl who is not prototypical, Ann would not necessarily see him as Cheerful and Boring. An alternative and equally viable interpretation is that the measure of Prototypicality represents mainly noise.

We expected that that perceivers' familiarity with a target should lead to lower levels of Prototypicality. However, looking within traits in Study 1, there was essentially a zero correlation with Prototypicality, the average correlation across the 20 traits being .049. Moreover, the correlation of Familiarity with average Prototypicality was .255, but the correlation is not significant ($p = .128$). We note that both of these correlations are positive, whereas our expectation was that they would be negative. However, in all three studies, an

extreme target effect, i.e., the target is liked or disliked, is associated with lower Prototypicality. Perhaps, for targets for whom there is more information, the perceiver effect is under-weighted, which implies lower Prototypicality.

Further evidence that the measurement of Prototypicality is problematic is its failure to correlate with its relevant SRM component. On average, its correlation is .260, whereas the other three components have much higher correlations, averaging .709. Additionally, only for six percent of the traits is Prototypicality more important than Volatility in determining Dissensus. Additionally, in Study 3, the only cue that correlates with Prototypicality is Attractiveness with Extraversion.

Nonetheless, three findings support the meaningfulness of the construct. The first result is the finding of a negative correlation between Prototypicality and Volatility in the two studies of first impressions. Because both Prototypicality and Volatility are, at least in part, errors in judgment, we might expect a positive correlation between the two, but that is not what is found. The implication appears to be that greater use of the perceiver effect in determining perceptions of a target is associated with lower use of the relationship effect. Second, and consistent with that negative correlation, there is evidence of a trade-off between Prototypicality and Volatility in their correlations. For example, the behavioral cues in Study 3 generally have positive correlations with Prototypicality and negative correlations with Volatility. The third result is the earlier-mentioned consistent negative effect of target extremity on Prototypicality. If a target is seen very positively or very negatively, Prototypicality effects are weaker.

Despite these three findings, the construct validity of Prototypicality is low. Low inter-trait correlations, relatively few correlations with individual difference variables and

behavioral cues, and the failure to correlate negatively with most familiarity and liking measures are consistent with the view of poor construct validity for Prototypicality.

Limitations

We urge caution in over-generalizing our conclusions. We have, in all three studies, fewer targets than perceivers, and sporadic and limited individual difference measures. Moreover, the analysis was not preregistered. Future research using the eSRM should be more focused on measuring relevant individual difference measures with preregistration. Moreover, we have speculated on the relationship between eSRM and SAM but have not conducted any empirical analyses.

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 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 non-consensual 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.

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 and whether the ordinary SRM can be employed. With our regression estimates, we do not know if the variation is

meaningful or just due to chance. In our analyses, we have found difficulties with Prototypicality, but we do not know if differences in that measure are meaningful or could be entirely due to error.

A third limitation is that we have exclusively focused on the half-block design. However, very often peer ratings use a round-robin design in which group member all rate each other. Ideally, once a more formal estimation procedure for the eSRM is developed, the round robin design could be analyzed using the eSRM.

Lastly, there are two possible extensions that we wish to mention. First, 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.

Additionally, all of our discussion and examples have targets as persons. However, targets might be situations or non-social 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.

Conclusion

For 40 years, SRM research has advanced the understanding of social perception. However, that model 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 paper, we address that limitation conceptually, statistically, and empirically.

Conceptually, we have argued that that disagreement and agreement are not opposites. Whereas the SRM focuses on agreement, both Assimilation and Consensus, the eSRM explores disagreement. We have shown that a perceiver's disagreement about targets, what we call Dissimilation, can be partitioned into Sensitivity and Differentiation and disagreement by perceivers about a target, what we call Dissensus, can be partitioned into Prototypicality and Volatility. Such a partitioning allows for a highly nuanced view of disagreement.

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

Empirically, we present results from three different studies. The empirical analysis clearly shows the utility of separating Dissimilation into Sensitivity and Differentiation, which in turn shed light on spread and Accuracy. We also separate Dissensus into Prototypicality and Volatility.

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

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Table 1

Hypothetical Ratings of Honesty Decomposed Using the Social Relations Model^a

Perceiver	Target					Means	<i>p</i>
	Art	Bob	Carl	Dave	Ed		
Ann	1.95 (1.45)	2.10 (0.10)	1.85 (-0.65)	4.80 (-0.20)	3.30 (-0.70)	2.80	-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	3.30	4.00	4.50	7.00	6.00	5.00	
<i>t</i>	-1.50	-1.00	-0.50	2.00	1.00		

^aPerceiver effects, *p*, in the row margin, target effects, *t*, in the column margin, and relationship effects in parentheses inside the cells of the table.

Table 2

The four elements^a of individual differences in disagreement in the perception of targets^b

Type	Level	
	Individual	Relationship
Dissimilation	Perceiver <i>Sensitivity</i> (q)	Perceiver <i>Differentiation</i> (g)
Dissensus	Target <i>Prototypicality</i> (k)	Target <i>Volatility</i> (h)

^aItalicization is used to indicate in the term primarily used for the element in the text.

^bThe term in parentheses is the symbol used for the element in the formal model.

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, Art and Carl, as a function of the perceiver effect

Appendix

Technical Issues

Here, we consider here three technical issues: the estimation of SRM variances for the half-block design, issues in the estimation of the eSRM by regression, 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 σ_p^2 , σ_t^2 , and σ_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 $(MS_P - MS_{P \times T})/n_t$, the estimate of target variance, s_t^2 , is given by $(MS_T - MS_{P \times T})/n_p$, and the estimate of perceiver by target or relationship variance, s_r^2 , is given by $MS_{P \times T}$. These are commonly called *ANOVA estimators* (Kenny, 2020). 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 identical, assuming all components are non-zero.

Issues in the Estimation of the eSRM by Regression

We have proposed a straightforward method of estimate the eSRM elements: the regression approach, as illustrated in Figure 1. Although this method of estimation is easy to understand, there are three drawbacks to this approach. First, using Dissimilation as an example, because the perceiver's data is 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 the perceiver and the target effects. Using the estimated, not actual, effects results 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 k and between the target effect or t and the target's Prototypicality or q . The presence of these correlations requires that the k and q slopes should be simultaneously estimated. For these reasons, the more formal estimates of the eSRM, once they are derived, are to be preferred.

Before we turn to these more advanced methods of estimation of the eSRM, we discuss the implications of our approach for accuracy. Within the standard SRM, the correlation of the correlation between a perceiver i 's judgment (i.e., X_{ij}) and the target effect (i.e., t_i), what we called *Accuracy*, equals $\sigma_i/\sqrt{\sigma_t^2 + \sigma_r^2}$. For the approach we used to estimate the eSRM, we use Equations 2 and 3 to measure Accuracy as:

$$\frac{k_i \sigma_t}{\sqrt{k_i^2 \sigma_t^2 + e^{g_i} \sigma_r^2}}.$$

Note that as the slope or k_i (i.e., Sensitivity) increases, accuracy increases, but as $e^{g_i} \sigma_r^2$ or Differentiation increases, accuracy declines. Because of the bias in the estimate of slopes, we used the empirical Bayes estimate, which equals $r_i(k_i - 1) + 1$, where r_i is the reliability of the estimated target effect which can be estimated by $s_t^2/(s_t^2 + s_r^2/n_p)$. To estimate the relationship variance, we use Differentiation squared for perceiver i . Because of the likely underestimation of the variance, we multiply it by $(n_t - 2)/(n_t - 3)$ where n_t is the number of 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) and Maydeu-Olivares & Coffman (2006)) have examined random intercepts in a factor analysis model and presumably, these approaches could be applied to estimate a model with differential slopes. Note though that this approach allows for variance in k slopes, but not the q 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.

To estimate the combined model of differential slopes and error variance is a difficult challenge. One possible estimation strategy would be Bayesian estimation. 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 are statistically justifiable.

Endnotes

¹As explained in numerous sources (e.g., Kenny, 2020), 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 paper, we mean *relationship plus error variance*.

²This equality exactly holds when the regression coefficient squared and the error variance are used to predict the variance in a perceiver's judgments, i.e., Dissimilation squared. However, because we use unsquared regression coefficient and the error standard deviation, there is not an exact correspondence.

³We used the Spearman-Brown prophecy formula, $kr_I/[1 + (k - 1)r_I]$ where k is the number of traits and r_I is the average inter-item correlation. For r_I , we used the average between-factor correlation.