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Assessing Clinically Relevant Perceptual Organization With Multidimensional Scaling Techniques

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Multidimensional scaling (MDS) techniques provide a promising measurement strategy for characterizing individual differences in cognitive processing, which many clinical theories associate with the development, maintenance, and treatment of psychopathology. The authors describe the use of deterministic and probabilistic MDS techniques for investigating numerous aspects of perceptual organization, such as dimensional attention, perceptual correlation, within-attribute organization, and perceptual variability. Additionally, they discuss how formal quantitative models can be used, in conjunction with MDS-derived representations of individual differences in perceptual organization, to test theories about the role of cognitive processing in clinically relevant phenomena. They include applied examples from their work in the areas of eating disorders and sexual coercion.

Cognitive theorists implicate individual differences in social information processing, particularly construal processes, in the development, maintenance, and treatment of various forms of psychopathology (Beck, 1976; Ellis, 1994; Kelly, 1955; McFall, 1982). Clinical scientists have had difficulty finding valid methods to assess social information-processing constructs, however. One promising solution draws on the theoretical and measurement models of cognitive science (McFall, Treat, & Viken, 1997, 1998). The purpose of this article is to illustrate the potential of this solution by focusing on the use of a specific method, multidimensional scaling (MDS), for investigating individual differences in perceptual organization, that is, the way in which persons organize and represent incoming stimulus information.

We first examine the conceptual strengths and methodological weaknesses of cognitive theory in clinical psychology. Next, we describe deterministic and probabilistic MDS models, which offer promise in overcoming some of these methodological limitations, and discuss their application to investigations of individual differences in perceptual organization. Finally, we describe the use of MDS to test hypotheses about the influence of perceptual organization on the operation of other cognitive processes. For illustrative purposes, we refer to two ongoing lines of research. The first is our investigation of individual differences in women's perceptions of information about other women's body size and affect and the links between these perceptions and eating disorders (Viken, Treat, Nosofsky, McFall, & Palmeri, in press). The second is our evaluation of individual differences in men's perceptions of women and the links between these perceptions and men's sexually coercive behavior (Treat, McFall, Viken, & Kruschke, 2001).

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Clinical-Cognitive Theory: An Exemplar

George A. Kelly's personal construct theory (1955) is a promising exemplar of a cognitive theory in clinical psychology. Of course, it is only one of many possible exemplars we might choose or cite. Beck's (1976) theory, for example, has had a greater influence on cognitive–behavioral therapists, and treatments based on Beck's theory have garnered an impressive record of empirical support (see Chambless & Ollendick, 2001). If we look beyond Kelly's idiosyncratic language, however, we find that his theory has more in common with contemporary cognitive science than many cognitive theories in clinical psychology. Thus, we believe that it provides a useful point of departure for building bridges between clinical science and cognitive science.

In the 40-plus years since its publication, Kelly's (1955) classic, two-volume opus, *The Psychology of Personal Constructs*, has exerted a significant metatheoretical influence on the areas of personality and clinical psychology. For example, the theory is featured prominently in many contemporary undergraduate textbooks in personality and clinical psychology. At the same time, however, the theory has had less influence on day-to-day experimental research in personality and clinical psychology. This disparity between the theory's metaphorical and empirical impacts reflects both its conceptual strengths and its methodological weaknesses.

On the conceptual side, Kelly was ahead of his time in focusing on individual differences in human information processing and on the influence such cognitive processes exert on human behavior.[1] Kelly's cognitive focus is set forth in the theory's *fundamental postulate*: "A person's processes are psychologically channelized by the ways in which he anticipates events" (p. 46).[2] This focus on cognitive processing is elaborated in a series of 11 corollaries, including the *construction corollary:* "A person anticipates events by construing their replications" (p. 50); the *individuality corollary:* "Persons differ from each other in their construction of events" (p. 55); the *commonality corollary:* "To the extent that one person employs a construction of experience which is similar to that employed by another, his psychological processes are similar to those of the other person" (p. 90); the *organization corollary:* "Each person characteristically evolves, for his convenience in anticipating events, a construction system embracing ordinal relationships between constructs" (p. 56); and the *dichotomy corollary:* "A person's construction system is composed of a finite number of dichotomous constructs" (p. 59). These postulates and corollaries, as elaborated in the remainder of Kelly's two-volume work, anticipated many ideas found in contemporary cognitive science.

On the methodological side, however, Kelly offered few research tools or experimental paradigms for testing his theory. Consequently, despite its prescient focus and abstract appeal, the theory has not lent itself readily to rigorous empirical tests, as required of good scientific theories (Popper, 1959). Personality and clinical psychologists have found it difficult, if not impossible, to operationalize, assess, and build quantitative models of the theory's hypothetical constructs and their nomological relationships (Cronbach & Meehl, 1955; MacCorquodale & Meehl, 1948; McFall & Townsend, 1998).

The Repertory Grid Technique (REP Test; Kelly, 1955) is the sole exception in Kelly's otherwise empty methodological toolbox. The REP Test is a novel assessment method designed to identify and map the relations among the bipolar core constructs in each individual's personal construct system. Unfortunately, despite efforts to refine, extend, and validate the REP Test, it has achieved only limited success (see Kihlstrom & Cunningham, 1991), largely because of the test's inherent problems. For example, the REP Test is used idiographically: Testees typically are instructed to supply the names of the particular individuals who fill the roles of specific "significant others" in their lives (e.g., mother, father, siblings, best friend, intimate partner). This idiographic method of generating test stimuli results in a unique stimulus set for each testee, which means that the test stimuli are not standardized. This, in turn, makes it almost impossible to conduct nomothetic analyses of test results or to make direct comparisons across individuals.

Furthermore, in the second step of the REP Test procedure, testees are instructed to consider subsets of "significant others" in groups of three and then to assign verbal labels to the ends of a bipolar personal construct dimension, labels that capture the most important ways in which the testee sees two of these people as "alike" and "different" from the third. This method of generating verbal labels for the testee's personal construct dimensions assumes that testees are capable of representing their constructs verbally.[3]

Finally, once a testee has generated a list of bipolar construct dimensions by considering the similarities and differences among numerous subsets of three "significant others," these construct dimensions and the ordinal relations among them must be quantified, analyzed, and interpreted. Unfortunately, there still is no satisfactory method of scoring, analyzing, and interpreting the REP Test's output, even though Kelly and his students devoted much of their effort to developing this aspect of the test (see Kihlstrom & Cunningham, 1991). Because the test results cannot be compared with norms and cannot be scaled quantitatively, they are of dubious value for generating quantitative interpretations and actuarial predictions.

Despite these limitations, the REP Test could be regarded, in retrospect, as a bold, innovative, and insightful attempt at assessing individual differences in personal construct systems. The underlying conception—namely that behavior is constrained by the way an individual construes situations—is full of promise. Unfortunately, until recently, the promise of this idea was lost in the translation from conception to measurement.

MDS Models of Perceptual Organization

MDS techniques provide a promising alternative for the assessment of individual differences in perceptual organization (Borg & Groenen, 1997; Davison, 1992; MacCallum, 1988; Schiffman, Reynolds, & Young, 1981). Numerous researchers across areas of psychology use MDS for data summary and reduction, but cognitive psychologists also view MDS as a useful tool for providing a "psychological model" of a person's perceptual representation, that is, a person's construal, to use Kelly's term (Nosofsky, 1992b). Unlike alternative strategies, the MDS approach does not assume that participants can report accurately on the characteristics of their perceptual representations. Moreover, MDS-derived characterizations of perceptual organizations can be compared meaningfully because all participants make judgments about the same set of stimuli. The parameters of MDS models also map well onto cognitive constructs of interest to clinical theorists, as we see in the remainder of this article. Cognitive psychologists have developed formal models of the way in which MDS-derived representations of perceptual organization can be used to predict performance on tasks assessing other cognitive processes, such as classification, memory, and learning. Thus, MDS models of perceptual organization have been incorporated by cognitive scientists into a coherent and elaborate set of theoretical and measurement models of human information processing.

Similarity ratings of all possible pairs of stimuli are the typical input to MDS algorithms. Other possible inputs are dissimilarity

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[1] Kelly resisted being characterized as a cognitive theorist. In fact, he resisted all efforts to "pigeon-hole" his theory. He felt that these labeling efforts were a form of stereotyping that led inevitably to distortions regarding the theory. His theory often was labeled "phenomenological," for instance; on seeing this label, people were inclined to assume that they now knew something important about his theory, even though they may not have read it and even though the theory differed in crucial ways from other theories with the same label. He wanted his theory to be read and appreciated as a distinctive approach to understanding human behavior, not merely as one member of any particular class of theories.

[2] Kelly's use of "he" reflects the customs of a different era, of course. We have chosen to retain his original wording for the sake of authenticity even as we recognize the potential effect of this decision on contemporary sensibilities.

[3] Paradoxically, Kelly emphasized elsewhere in his books that some of the most important personal constructs often tend to be preverbal.

ratings and matrices containing the frequency of same–different judgments or identification confusions (i.e., the frequencies with which each stimulus is misidentified, or "confused," with every other stimulus). In our own studies of eating disorders, for example, we first created a stimulus set of 24 photographs of undergraduate women who varied in body size and facial affect. We then asked participants to rate the similarity of all possible stimulus pairs (276 pairs; $n * (n - 1)/2$) on a 10-point scale ranging from 1 (*very different*) to 10 (*very similar*). Finally, we used MDS to obtain a spatial representation of participants' perceptual organizations. Panel A in Figure 1 presents a scaling solution, or "psychological space," for these 24 stimuli, in which interstimulus distance decreases as perceived similarity increases. Thus, two stimuli judged to be very similar were scaled closer together than two stimuli judged to be very dissimilar.

The remainder of the article provides an overview of both deterministic and probabilistic MDS models. Deterministic models assume that stimulus perception does not fluctuate across trials (i.e., that stimulus values are perceived very precisely). For example, the body size of the same woman might be perceived very similarly across presentations. Thus, deterministic methods represent stimulus perception as a single fixed value. In contrast, probabilistic models assume a random component to participants' perceptions, whereby stimulus values or their differences are perceived variably across trials (e.g., perception of body size might vary on each presentation, creating a distribution of perceived body-size values). The probabilistic scaling model discussed in this article, PROSCAL (MacKay, 1989, 2001; MacKay & Zinnes, 1986; Zinnes & MacKay, 1983, 1992), accommodates this perceived variability by treating stimulus perception as a distribution of values rather than as a single fixed value. We discuss the strengths and weaknesses of these two approaches as well as the conditions under which they should be used as we proceed.

Deterministic MDS Models

One of the strengths of deterministic MDS methods lies in their simultaneous representation of both shared and unshared aspects of construal processes across individuals and stimuli. In the most general MDS model, some parameters capture differences between individuals (i.e., they are estimated separately for each individual), some parameters represent differences between stimuli (i.e., they are estimated separately for each stimulus), and some parameters remain fixed across individuals and stimuli (i.e., they are assumed

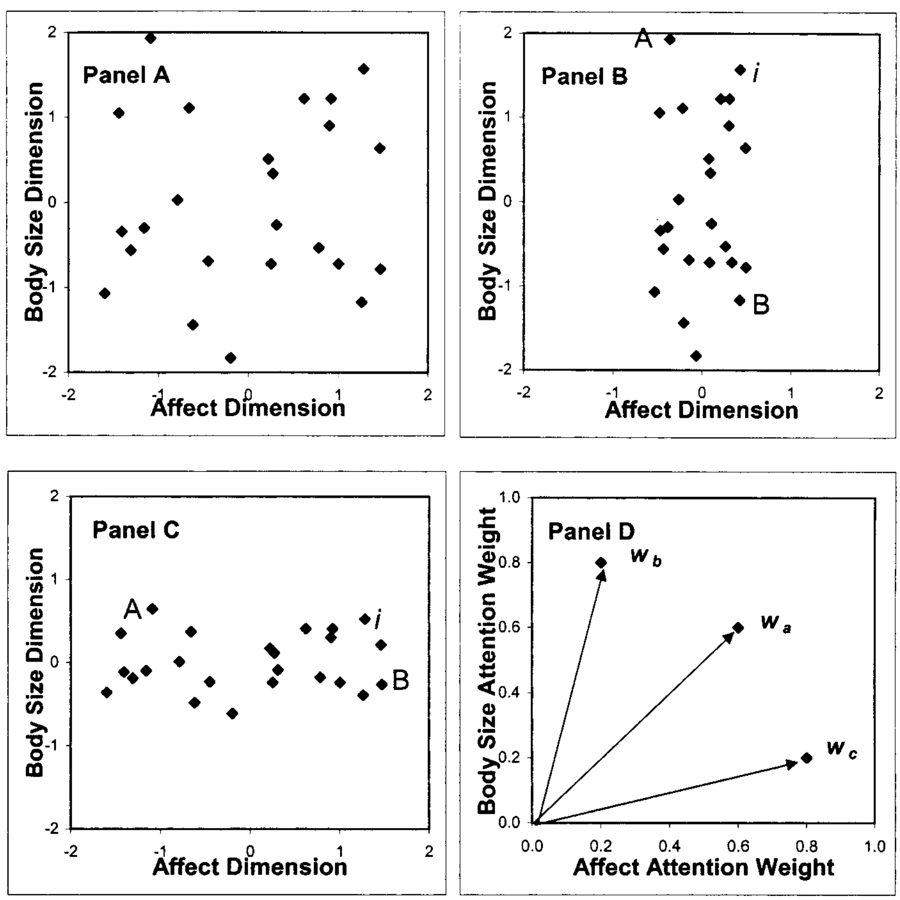

Figure 1. Panel A presents a hypothetical two-dimensional scaling solution for photographs of women varying along body-size and affect dimensions; Panels B and C illustrate hypothetical perceptual organizations for body-size-oriented and affect-oriented participants, respectively, and also show Prototypes *A* and *B* as well as stimulus *i*, which is to be classified; Panel D illustrates 3 participants' attention weight vectors in a hypothetical subject space.

to be the same for all individuals and stimuli). This approach instantiates nicely the theoretical expectation that both normal and abnormal construal processes can be characterized by differing parameter values within a single model. Next, therefore, we must acquaint ourselves with some of the parameters of the most general deterministic scaling model—coordinates, subject weights, and dimensional correlations—and with two common constrained versions of this model, in which only a subset of the parameters in the general model is estimated.

In 1984, Young proposed the most general deterministic scaling model of the perceived dissimilarity of stimuli i and j by participant k, d_{ijk} (cf. Young, 1987). Participants typically find it easier to make similarity ratings than dissimilarity ratings, but MDS algorithms conventionally model dissimilarities. Reversing (i.e., reflecting) participants' similarity ratings provides the necessary dissimilarity data (e.g., $10 = 1$, $9 = 2$, etc.), in which larger values indicate greater perceived dissimilarity. For ease of exposition, we refer to these reversed similarity ratings as dissimilarity ratings throughout the remainder of the article. According to the general Euclidean model, the dissimilarity rating, d_{ijk}, is a function of the weighted Euclidean distance between the two stimuli, δ_{ijk}, along r dimensions[4]:

$$\delta_{ijk} = [(x_i - x_j)(V_i W_k)(x_i - x_j)^T]^{1/2}.$$

Both x_i and x_j are r-dimensional row vectors containing the *coordinates* of particular points i and j in an r-dimensional space. Both V_i and W_k are $r \times r$ matrices: V_i contains dimension-specific *stimulus weights* for stimulus i, and W_k contains dimension-specific *subject (or attention) weights*, which we discuss in detail later. Two commonly used deterministic models are constrained versions of this general model: (a) the weighted MDS model (WMDS) (also known as the INDSCAL model; Carroll & Chang, 1970; Carroll & Wish, 1974); and (b) Tucker's (1972) correlational model. Both special cases discussed here treat V_i as an identity matrix, but interesting models also emerge from relaxing this constraint (see Young, 1987).

The WMDS Model: Quantifying Individual Differences in Dimensional Attention

According to the WMDS model, individual participants perceive the relative positioning of the stimuli along each dimension of the group's configuration in the same way, but each individual stretches and shrinks these dimensions differentially. Technically, WMDS represents individual differences in the importance of stimulus dimensions to participants' similarity ratings by estimating individual-specific attention weights for each dimension of the group's multidimensional space. This model is a special case of Young's (1984) general Euclidean model, when V_i is an identity matrix and W_k is a diagonal matrix (Carroll & Chang, 1970; Carroll & Wish, 1974; see also Takane, Young, & de Leeuw, 1977).

Panels B and C in Figure 1 present two possible transformations of the group configuration shown in Panel A of Figure 1; both are consistent with the WMDS model. Panel B shows the perceptual organization of an extremely "body-size-oriented" (BSO) participant, who placed much more importance on body size than on affect when making her similarity ratings. The WMDS model represented her differential weighting of body size and affect by stretching the group configuration along the body-size dimension and shrinking it along the affect dimension. This transformation captured her perception that heavy and light stimuli were much more dissimilar than happy and sad stimuli. In contrast, an extremely "affect-oriented" (AO) participant, as depicted in Panel C, showed a large attention weight for affect and a small attention weight for body size, reflecting her perception of happy and sad stimuli as much more dissimilar than heavy and light stimuli.

Each participant's attention weights specify the end point of a participant-specific vector in an r-dimensional "subject space," which is depicted in Panel D of Figure 1. The two dimensions of the subject space correspond to the magnitude of the attention weights for affect and body size, respectively. The number of vectors in the subject space indicates the number of participants in the sample (three in this example). Vector direction indicates the participant's relative attention to the stimulus attributes, and vector length specifies the fit of the model to a participant's data (i.e., the degree to which the specified dimensions explain the participant's judgments). A participant who attended relatively more to body size than affect, such as shown in Panel B, would be represented in the subject space by a vector directed toward the upper left region of the space, such as w_b. In contrast, a participant attending relatively more to affect than to body size, as shown in Panel C, would be represented in the subject space by a vector such as w_c. Vector w_a represents a participant who attended similarly to affect and body size; this participant's perceptual organization would resemble that presented in Panel A. The similar length of these three vectors indicates the similar fit of the WMDS model to the three participants' judgments, but their differing directions indicate the marked discrepancy in their relative attention to the stimulus attributes.

"Flattened subject weights" (FSWs) quantify individual differences in relative attention to pairs of stimulus attributes by transforming each pair of attention weights into a single index of relative attention (MacCallum, 1977; Schiffman et al., 1981; Young & Lewyckyj, 1996). In our case, positive values reflect greater attention to dimension one (affect) and negative values reflect greater attention to dimension two (body size). Thus, in Panel D of Figure 1, vectors directed toward the lower right corner of the subject space, such as w_c, receive positive FSWs; vectors directed toward the upper left corner, such as w_b, receive negative FSWs; and vectors such as w_a receive FSWs near zero.

Tucker's Correlational Model: Quantifying Individual Differences in Dimensional Correlation

Additional individual-specific parameters become available for investigation in a second constrained version of Young's (1984) general Euclidean model, in which off-diagonal elements of W_k can be nonzero. Tucker's (1972) correlational model allows individual-specific correlations between the axes of the group

[4] Under some conditions, it is more appropriate to assume a city-block, rather than a Euclidean, distance metric (Nosofsky & Palmeri, 1996; Shepard, 1964, 1987). Researchers generally assume that the city-block metric underlies judgments of stimuli with readily separable dimensions, whereas the Euclidean metric underlies judgments of integral stimuli, which are perceived in a more holistic fashion. The Euclidean distance metric is used in all analyses reported here because it consistently resulted in better fits than the city-block metric for our stimulus sets.

space in addition to individual-specific weights on the group perceptual axes. Figure 2 depicts the perceptual organizations of three participants who placed similar importance on body size and affect when making their similarity ratings but who varied in their perception of the association between body-size and affect information. The first participant, shown in the left panel, perceived affect and body-size information to be uncorrelated. In contrast, the second participant, shown in the middle panel, perceived these two types of information to be associated positively, such that heavier women were more likely to be perceived as happy and lighter women as sad. The third participant, shown in the right panel, perceived a negative relationship between the two attributes and tended to perceive heavier women as sad and lighter women as happy. This example assumed that the attention weights for body size and affect were similar for all three participants, but these parameters also are free to vary across individuals in Tucker's model. Thus, both the WMDS model and Tucker's model allow individual differences in participants' weighting of the dimensions of a common group configuration, but Tucker's model generalizes the WMDS model by adding participant-specific correlations as well.[5]

Summary

Deterministic MDS models can be used to assess individual differences in perceptual organization in a more quantitative, theoretically coherent, and performance-based fashion than is feasible with existing clinical measures, such as Kelly's (1955) REP Test (Jones, 1983; Rudy & Merluzzi, 1984). Scaling solutions appear to operationalize well the "construct system" to which Kelly referred in his construction and organization corollaries. The WMDS model and Tucker's correlational model neatly instantiate Kelly's commonality and individuality corollaries by representing simultaneously both the shared and the individual-specific aspects of construal processes. In addition, these perceptual representations can be derived without relying on participants' introspective verbal reports of how they are processing information.

In the next section, we discuss the application of these MDS models to questions of interest to clinical scientists. Clinical and social psychological investigators commonly have used MDS methods in an atheoretical, exploratory fashion in the hope of discovering or revealing unknown dimensions underlying social perception (see Jones, 1983, for a review). In contrast, we recommend using MDS methods in the theory-driven, hypothesis-testing approach more characteristic of cognitive scientists, who typically use structured, well-defined stimuli for which the underlying dimensions influencing participants' perceptions are known in advance. We extend the typical approach of cognitive scientists, however, by focusing simultaneously on normative and individual-specific aspects of perception and by using more socially relevant stimuli.

Using Deterministic Scaling Approaches to Evaluate Clinically Relevant Perceptual Organization

MDS measurement models can be used to evaluate theoretical expectations about individual differences in at least three characteristics of participants' perceptual organizations: (a) attention to stimulus attributes; (b) perceived correlation between stimulus attributes; and (c) intradimensional attribute organization. We illustrate the use of MDS methods to address research questions relevant to these three characteristics with both empirical and hypothetical examples drawn from our investigations into the role of cognitive processing in eating disorders.

Individual Differences in Attention to Stimulus Attributes

Cognitive theorists have argued that women exhibiting problematic eating patterns attend more than control participants to information related to shape, weight, food, and eating (Vitousek, 1996; Vitousek & Hollon, 1990; Williamson, Muller, Reas, & Thaw, 1999). We hypothesized that this preoccupation should result in relatively less attention to other potentially important information, such as facial affect. To test this hypothesis, we developed a stimulus set specifically designed to assess individual differences in women's relative attention to other women's body size and affect. Undergraduate females were photographed wearing black tights and a white T-shirt while standing in front of a neutral background. A separate group of undergraduate females provided normative ratings of the body size and affect of the woman in each stimulus photo. We used these ratings to construct a final stimulus set, in which stimuli were distributed fairly uniformly across the two-dimensional psychological space and the correlation between the normative ratings for affect and body size was near zero. Although this stimulus development process was somewhat tedious and time consuming, it was well worth the effort in terms of the strength and precision of the inferences it allowed us to make. By standardizing clothing and background, we focused variation in the stimulus set on the two attributes of interest. By also allowing numerous other attributes to vary across stimuli (e.g., hair color, attractiveness), we produced a well-defined, but ecologically valid, set of photographs. By selecting stimuli such that there was a negligible correlation between the attributes of interest, we ensured that our estimates of attention to these attributes were relatively independent.

We used this stimulus set to investigate the hypothesized links between eating disorders and relative attention to body size and affect. Undergraduate women who reported either many or few symptoms of bulimia on a mass screening questionnaire completed a similarity-ratings task with these stimuli (Viken et al., in press). The WMDS model was used to evaluate whether bulimic and control participants showed differential attention to body size and affect. We adopted a confirmatory, rather than an exploratory, approach because we were using WMDS to test specific hypotheses about perceptual differences in a highly structured stimulus set. We constrained the two-dimensional solution to correspond to the normative ratings for body size and affect, and we estimated attention weights only for body size and affect in the MDS analysis (i.e., stimulus coordinates were fixed rather than estimated). As expected, bulimics, relative to controls, showed significantly larger attention weights for body size, significantly smaller attention

[5] IDIOSCAL (Carroll & Chang, 1972), an alternative MDS model, also relaxes the diagonality constraint on W_k and is mathematically equivalent to Tucker's correlational model. IDIOSCAL provides an alternative interpretation of what is varying across individuals, however, by estimating individual-specific orthogonal rotations of the group's configuration as well as individual-specific weights on these rotated dimensions, or "directions." Thus, IDIOSCAL captures individual differences in the location of participants' primary perceptual axes in the group psychological space.

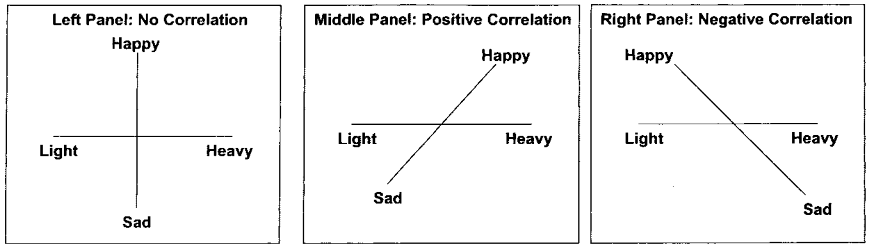

Figure 2. Three participants' perceptions of body size and affect. The left, middle, and right panels illustrate no correlation, positive correlation, and negative correlation, respectively.

weights for affect, and significantly more negative FSWs.[6] In other words, the BSO perceptual organization shown in Panel B of Figure 1 was more typical of bulimics, whereas the AO organization depicted in Panel C was more characteristic of controls. In the subject space shown in Panel D, bulimics' vectors tended to point toward the upper left corner, whereas controls' vectors tended to point toward the lower right corner. A separate study of 30 undergraduate women demonstrated that these attention weights were highly stable over a 2-week period when assessed under highly similar conditions; test–retest correlations for affect and body-size attention weights were .81 and .75, respectively (Viken, Treat, & Vazquez, 1996).

Individual Differences in Perceived Correlation Between Stimulus Attributes

In future studies, we plan to use Tucker's correlational model to evaluate whether bulimics perceive body size (light to heavy) and affect (sad to happy) to correlate more negatively than controls, particularly under conditions likely to increase symptomatic behavior (e.g., after consumption of taboo food or an experience of negative interpersonal evaluation). Referring back to Figure 2, we would expect that the right panel best characterizes bulimics' perceptual organizations, whereas the left panel best approximates controls' organizations.

Individual Differences in Intradimensional Attribute Organization

We also plan to examine whether bulimics perceive body size in a more categorical, "all-or-none" fashion. Suppose, for example, that participants rated the similarity of the body size of the women in the photos, and we estimated a unique one-dimensional solution for each participant. Then we could quantify for each participant the extent to which stimuli were distributed evenly across the body-size dimension, as in the lower half of Figure 3, rather than being clustered into discrete subgroups, as in the upper half of Figure 3.[7]

The deterministic MDS models discussed thus far assume that stimulus perception does not vary across trials and that it can be represented as a fixed value in psychological space rather than as a distribution of values. However, perceptual variability may be the rule rather than the exception in many circumstances of interest to clinical scientists. Under these circumstances, consideration of probabilistic MDS models, which represent this variability explicitly, may be beneficial.

Probabilistic MDS Models

Probabilistic scaling models are well suited for circumstances in which intra- or interindividual perceptual variability or stimulus confusability is present. In both cases, stimulus values are perceived variably across trials. Perceptual variability may play an important role when investigating perceptual organizations of patient populations with marked cognitive impairment, such as with schizophrenia or dementia. Alternatively, perceptual variability might result from alcohol consumption, anger, fatigue, or other transient influences on cognitive processing.[8] Marked stimulus confusability might occur when stimuli are very similar to one another, the duration of stimulus presentation is very short, or stimulus quality is degraded. Probabilistic methods should provide more valid estimates of stimulus coordinates under these circumstances. Additionally, the variance estimates may be of intrinsic interest to investigators because they could vary meaningfully as a function of the stimulus, the stimulus dimension, personal characteristics, or relevant manipulations. For example, individual differences in the magnitude of the variance estimates might be a useful indicator of the extent of cognitive impairment.

Given the uniqueness and complexity of the various probabilistic scaling models, we focus here on one probabilistic scaling model: PROSCAL (MacKay, 1989, 2001; MacKay & Zinnes, 1986; Zinnes & MacKay, 1983, 1992). PROSCAL's unique ability

[6] Alternatively, we could have evaluated this hypothesis using a multiple regression approach, in which separate, unconstrained two-dimensional solutions were estimated for each participant and the resulting coordinates were regressed onto the normative ratings for body size and affect in two separate regression analyses (see Chapter 12 in Schiffman et al., 1981, and Chapter 8 in Davison, 1992). The resulting multiple *R*s for body size and affect are similar conceptually to the attention weights for body size and affect that were estimated using the constrained WMDS approach. In our experience, the multiple regression approach results in slightly more reliable group differences, particularly when some correlation is present between the normative ratings for the stimulus dimensions. We typically adopt the constrained WMDS approach, however, because of the greater ease of implementation and the relative independence, by design, of normative ratings for affect and body size in our stimulus set.

[7] Cluster-analytic techniques also might be applied profitably to participants' similarity ratings here because individual differences in weights applied to the resulting clusters might provide related information (Arabie, Carroll, & DeSarbo, 1987; Carroll & Chaturvedi, 1995).

[8] In some cases, the variance estimates also may be capturing perceptual uncertainty, rather than perceptual variability, which occurs when the observer has no idea what an object's scale value may be on a given dimension.

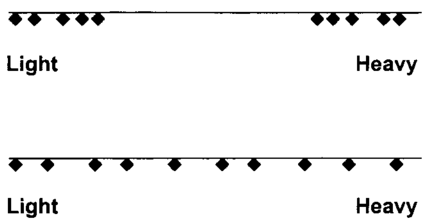

Figure 3. Participants' perception of body size. The upper half illustrates "clumped" perception of body size as either heavy or light, whereas the lower half depicts more graduated perception of body size.

to account for differential variability in stimulus perception makes it particularly appropriate for the applications described later. PROSCAL[9] provides a multidimensional generalization of Thurstone's (1927) unidimensional probabilistic scaling model. Perception of each stimulus i is assumed to follow a multivariate normal distribution, and unique maximum likelihood estimates of mean and variance parameters may be obtained for each stimulus on each of r dimensions. The $r \times r$ covariance matrix, Σ_i, contains all of the variances and covariances associated with a particular stimulus. These variance estimates are assumed to reflect either intraindividual differences in perceived stimulus locations, when judgments from a single person are analyzed, or both intra- and interindividual differences in perception, when multiple participants' judgments are analyzed simultaneously.[10]

Four restricted versions of the full PROSCAL model, which place constraints on the stimulus covariance matrices, commonly are estimated in practice. These submodels result from specifying whether variance estimates differ *within* a dimension (i.e., Case V vs. Case III models) and whether variance estimates differ *across* dimensions (i.e., isotropic vs. anisotropic models). Following Thurstone's (1927) nomenclature, Case V models estimate the same variance for all stimuli within a dimension (e.g., variability in perception of body size is constant across stimuli), whereas the more general Case III models estimate a variance for each stimulus within a dimension (e.g., variability in perception of body size is stimulus specific). The second distinction specifies whether variances differ across dimensions. Now following MacKay's (1989) terminology, *isotropic* models estimate the same variance across dimensions for a particular stimulus (e.g., variability in perception of body size and affect is the same for a particular stimulus). In contrast, *anisotropic* models estimate different variances across dimensions for a particular stimulus (e.g., variability in perception of body size and affect differs for a particular stimulus), and these variances may or may not be correlated. Factorial combination of the case and tropic distinctions results in four possible variance structures, which Figure 4 illustrates: Case V isotropic (Panel A), Case III isotropic (Panel B), Case V anisotropic (Panel C), and Case III anisotropic (Panel D).

In many cases of interest to clinical scientists, perceptual variability may be consistent with a Case III anisotropic variance–covariance structure. For example, we might expect that bulimics' perceptions of light stimuli are more precise than their perception of heavy stimuli and that their perception of body size is more precise overall than their perception of affect. Figure 5 illustrates this hypothesized perceptual organization. This Stimulus $\times$ Dimension interaction in variance estimates corresponds to a Case III anisotropic variance–covariance structure. Similarly, we might anticipate that men who exhibit sexually coercive behavior would perceive variability in women's sexual interest less precisely than variability in the provocativeness of their dress, particularly when provocativeness-of-dress is marked.

Probabilistic models are at a clear advantage over deterministic models when estimating stimulus configurations in which stimulus variances are large relative to interstimulus distances, particularly when variances differ by stimulus or dimension (Zinnes & MacKay, 1983). PROSCAL disentangles perceptual variability from interstimulus distances, whereas deterministic models confound these two influences on participants' judgments. Deterministic models assume that the scaled interstimulus distances increase monotonically with participants' dissimilarity judgments. Thus, deterministic methods misconstrue large dissimilarity judgments resulting from large perceptual variability as indicators of large interstimulus distances. In the extreme case, in which stimulus variability far exceeds interstimulus distances, the magnitude of the perceptual variability can determine almost entirely the stimulus locations estimated by deterministic methods.[11]

[9] PROSCAL and relevant publications can be downloaded at http://proscal.com.

[10] The variance estimates also presumably reflect whatever decisional variability is present. In part to separate perceptual and decisional contributions to parameter estimates, MacKay added a measurement model to PROSCAL, which relates participants' similarity judgments to underlying dissimilarities using additive, scale, and exponent constants (for details see PROSCAL manual at http://proscal.com). This decision-making model is simplistic, however, and it is doubtful that its inclusion completely eliminates the influence of decisional variability on perceptual parameter estimates.

[11] Understanding the advantages of the probabilistic model necessitates grasping the distinction between three distance measures used in the model: the participant's dissimilarity judgments, d_{ij}, the scaled distances, δ_{ij}, and the expected distances $E(d_{ij})$. Transformations of the participant's dissimilarity judgments, d_{ij}, are assumed to correspond directly to the perceived Euclidean (or city-block; see MacKay, 2001) distance between the two stimuli. Perception of x_i and x_j is expected to vary on a trial-by-trial basis, so d_{ij} also varies trial by trial. In contrast, δ_{ij} is the scaled distance between μ_i and μ_j, the mean percepts of stimulus i and j; δ_{ij} is not a random variable and does not change from trial to trial. Finally, $E(d_{ij})$ is the expected value of the participant's dissimilarity judgments, d_{ij}. According to the PROSCAL model, $E(d_{ij}) \rightarrow \delta_{ij}$ as the ratio of interpoint distances to stimulus variances increases. As the stimulus variances approach infinity, however, $E(d_{ij}) \rightarrow \infty$, even as $\delta_{ij} \rightarrow$ zero. To appreciate this property, note that if two stimuli have identical means (i.e., $\delta_{ij} = 0$) and nonzero variances, all of the judgments will be positive.

In sum, according to the PROSCAL model, both participants' dissimilarity judgments and the expected distances should increase as the stimulus variances increase. Except in a Case V isotropic situation, however, the scaled distances should not increase monotonically with participants' dissimilarity judgments and the expected distances. PROSCAL earns its advantage over deterministic methods by treating transformations of the expected distances as the best model of participants' judgments. In contrast, deterministic models treat transformations of the scaled distances as the best model of participants' dissimilarity judgments and erroneously conclude that large dissimilarity judgments resulting from large perceptual variability are due to large differences in stimulus locations. Thus, probabilistic models are at a clear advantage over deterministic models when marked perceptual variability or stimulus confusability is present, particularly when Case III or anisotropic variance structures hold. Stated differently, if the researcher believes that some stimuli or dimensions are perceived more uniformly than others, probabilistic models, such as PROSCAL, should be used.

Zinnes and MacKay (1983) illustrated the limits of deterministic methods in the presence of noise in a classic hexagon simulation. They created a two-dimensional configuration containing 12 points; 6 formed an interior hexagon, and 6 formed an exterior hexagon (see Panel A of Figure 6). Variances for stimuli on the interior hexagon were substantially greater than variances for stimuli on the exterior hexagon. Thirty replications of all interpoint distances were simulated and subjected to deterministic analysis by KYST (Kruskal, 1964; Kruskal & Wish, 1978) and probabilistic analysis by PROSCAL. As expected, PROSCAL recovered the true configuration well (see Panel C of Figure 6), whereas KYST incorrectly reversed the hexagons (see Panel B of Figure 6). The failure of KYST to recover the true configuration was attributed to its systematic misattribution of the large simulated *variances* associated with the inner hexagon to large interpoint *distances.*[12]

Explicit representation of perceptual variability in PROSCAL enhances the precision of MDS-derived maps of participants' perceptual organizations when marked inter- or intraparticipant variability in perception is present. Specification of an error model also facilitates hypothesis testing about dimensionality and the equality of stimulus locations and variances because both types of hypotheses can be tested using chi-square nested-model comparisons (Wickens, 1982) or information-criterion statistics (Akaike, 1974; Bozdogan, 1987). Researchers using deterministic models, in contrast, frequently cannot draw strong conclusions about dimensionality and constrained solutions by comparing different models' fit indices statistically. Thus, researchers often resort to qualitative strategies to determine dimensionality and speculate about whether the improved fit of a less constrained configuration is substantial enough to warrant rejection of the restricted model.[13]

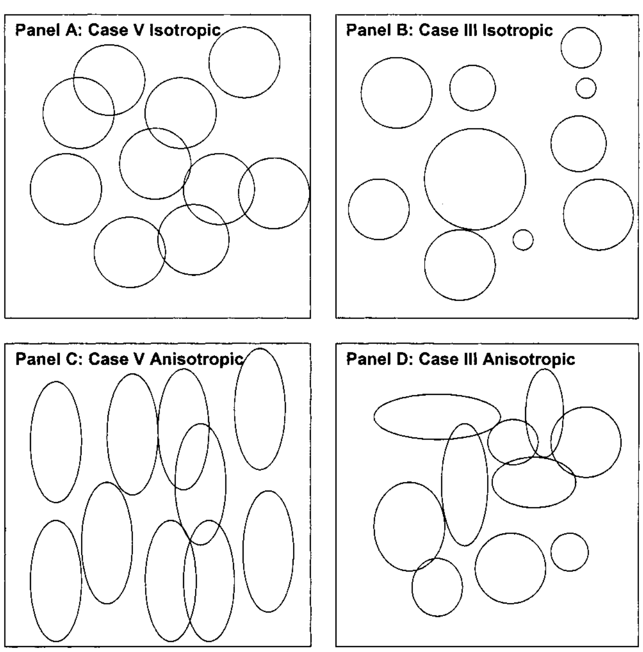

Figure 4. Four possible variance–covariance structures for 10 stimuli varying along two dimensions. The ellipses are referred to as *equal-likelihood contours,* which are composed of all points lying 1 standard deviation from the mean of the multivariate normal distribution for a particular stimulus. Panel A depicts a Case V isotropic structure, in which variance estimates are the same for all stimuli along both dimensions; Panel B presents a Case III isotropic structure, in which the variance estimates differ by stimulus but not by dimension; Panel C shows a Case V anisotropic structure, in which the variances differ by dimension but not by stimulus; and Panel D depicts a Case III anisotropic structure, in which the variances differ by both stimulus and dimension.

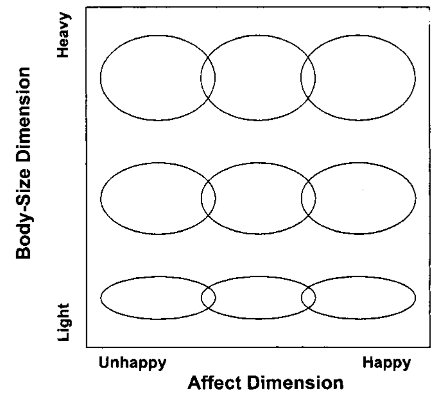

Figure 5. Illustrative hypothetical representation of bulimics' perceptual organization of body-size and affect stimulus information, in which body size is perceived more precisely when small and body size is perceived more precisely overall than affect.

The advances resulting from probabilistic representation of perceptual organization sometimes are costly, however, because the increased number of free parameters necessitated by estimation of complex variance structures (e.g., Case III, which estimates stimulus-specific variances) places greater demands on the data submitted for analysis. If a simple variance structure is assumed, however, PROSCAL estimates only a few additional parameters (e.g., one for the Case V isotropic structure and *r* for the Case V anisotropic structure). Additionally, deterministic methods typically overestimate dimensionality in simulation studies, so PROSCAL solutions often estimate fewer parameters than deterministic methods (MacKay & Dröge, 1990; MacKay & Zinnes, 1986, 1988).

Nonetheless, PROSCAL's developers have reduced the number of free parameters, in part, by excluding individual-specific parameters from simultaneous analyses of multiple participants' data. Thus, replicated judgments are critical to reliable parameter estimation from a single participant's data, if individual-specific inferences about perceptual organization are of greatest interest and a complex variance structure is assumed. Group-specific inferences require fewer judgments from each participant, but variance estimates reflect both inter- and intraindividual differences in the perceived locations of stimuli. The ideal solution to this dilemma will necessitate extending PROSCAL to allow individual-specific estimation of a subset of model parameters. In the interim, researchers can increase the precision and interpretability of these

[12] Fortunately, the fit of KYST to data that are grossly inconsistent with a deterministic model should be extremely poor, and researchers would have little reason to take seriously the estimated configuration.

[13] Nosofsky (1985) illustrated how restricted versions of deterministic MDS models could be evaluated using likelihood-ratio methods, however, by estimating the scaling solutions within an MDS-choice model framework.

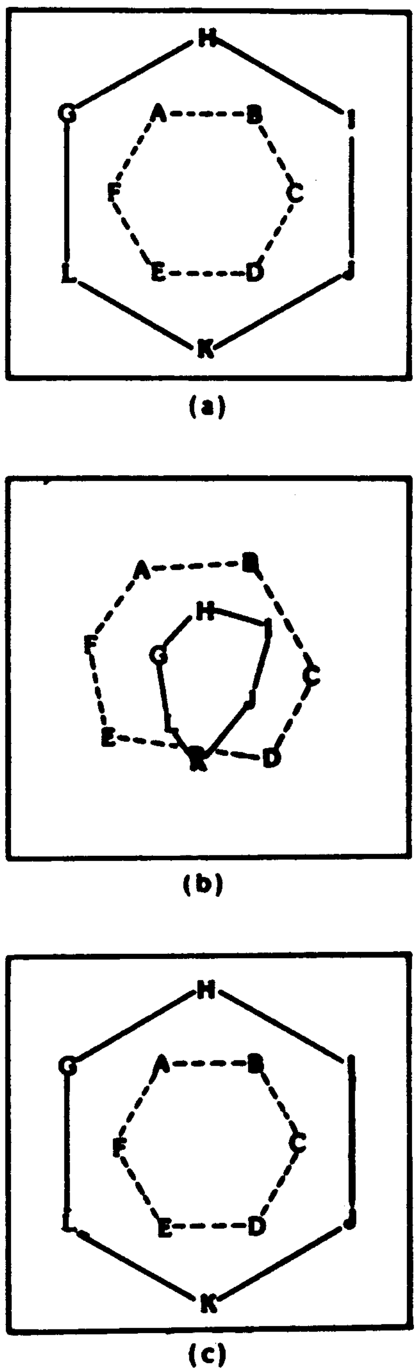

Figure 6. Results of Zinnes and MacKay's (1983) hexagon simulation. (a) The configuration used to simulate distances; stimuli in the inner hexagon were characterized by substantially larger variance estimates than stimuli in the outer hexagon. (b) and (c) Best solutions estimated by KYST and PROSCAL, respectively. From "A Probabilistic Multidimensional Scaling Approach: Properties and Procedures," by J. L. Zinnes and D. B. MacKay, in *Multidimensional Models of Perception and Cognition* (p. 48), edited by F. G. Ashby, 1992, Hillsdale, NJ: Erlbaum. Copyright 1992 by Erlbaum. Reprinted with permission.

group- and individual-level parameter estimates by making every effort to minimize perceptual variability resulting from factors that are not of primary theoretical interest.

Using Probabilistic Scaling Approaches to Evaluate Clinically Relevant Perceptual Organization

Not surprisingly, PROSCAL estimates parameter values better than deterministic methods when simulated data are generated explicitly by a probabilistic model. A more stringent evaluation of the incremental utility of probabilistic approaches necessitates demonstrating that (a) PROSCAL detects the presence of perceptual variability in real data, when theoretically it is expected to be present (e.g., when participants are subjected to an alcohol manipulation) and (b) parameter estimates from the probabilistic and deterministic analyses show predictable, systematic discrepancies (i.e., stimuli estimated by PROSCAL to have larger variances are scaled closer to the exterior of the deterministic space than the probabilistic space).

We provided such an evaluation of the potential utility of probabilistic scaling approaches with clinically relevant, nonsimulated data in the following pilot study, which was designed to examine the effect of alcohol consumption on individual differences in men's perceptions of women (McFall, Treat, & Viken, 1999; Treat, MacKay, & Nosofsky, 1999). Fourteen male participants older than 21 years were assigned randomly either to an alcohol condition, in which they consumed enough alcohol to raise their breath alcohol level to approximately .05, or to a placebo condition, in which they were told they would consume alcohol but consumed a nonalcoholic beverage instead. Participants consumed and absorbed their beverage and then rated the similarity of all possible pairs of 14 photos of women, which were selected to vary along dimensions such as provocativeness, affect, appeal, approachability, and attractiveness.

Group-level analyses were carried out because individual participants did not provide enough judgments to warrant participant-specific probabilistic analyses. All analyses assumed a Euclidean metric and a two-dimensional configuration. ALSCAL[14] (Young & Lewyckyj, 1996) was used for deterministic analyses, and PROSCAL was used for probabilistic analyses. Final PROSCAL analyses assumed a Case III anisotropic variance structure because estimation of this complex variance structure improved model fit significantly. Four scaling solutions were estimated, one for each combination of condition (alcohol or placebo) and MDS model (ALSCAL or PROSCAL). Each configuration was transformed such that (a) it was centered around zero and (b) the sum of the squared coordinates was equal to the number of stimuli. These transformations made the centroid of each configuration zero and the ranges of the solutions comparable. In all cases, the stimulus dimensions estimated by the two models were interpretable as appeal and provocativeness.

The variances estimates from the PROSCAL analysis were readily interpretable. Alcohol participants showed significantly larger variance estimates than placebo participants, $t(27) = 1.733$, $p < .05$, $ES = .32$, which is consistent with evidence that alcohol disrupts cognitive performance (Finnigan & Hammersley, 1992).

[14] ALSCAL is available in the SPSS statistical package and also can be downloaded at http://forrest.psych.unc.edu/.

Additionally, variance magnitude was related strongly to our subjective sense of either how easily a stimulus could be placed along the dimension or the likely magnitude of individual differences in placement of the stimulus (given that a large variance estimate could reflect either or both). For example, in both the alcohol and placebo participants' analyses, seminude stimuli showed a small variance along the provocativeness dimension but a large variance along the appeal dimension. This was in keeping with our judgment that these photos consistently were viewed by college males as provocative but there was much less consensus about how appealing they were.

Our concerns about the distorting effect of perceptual variability on the deterministic scaling solutions were well founded, as indicated by visual inspection of the untransformed probabilistic and deterministic scaling solutions for alcohol and placebo participants, shown in Figure 7. In marked contrast to the probabilistic scaling solutions, the deterministic solutions in the lower half of the figure were characterized by a large empty interior region. In other words, stimuli in the deterministic scaling solutions were scaled closer to the exterior of the space. This qualitative finding is consistent with the results of several stimulation studies, such as the hexagon example described earlier (Zinnes & MacKay, 1983), in which deterministic methods scaled higher variance stimuli toward the exterior of the space. To evaluate this effect quantitatively, we calculated for each stimulus the ratio of its distance from the centroid of the deterministic analysis to its distance from the centroid of the probabilistic analysis; this computation was completed separately for alcohol and placebo participants' solutions. We expected that stimuli that were scaled *farther* from the centroid of the deterministic than the probabilistic solution (i.e., those stimuli with ratio scores > 1.0) would show significantly greater variances than those stimuli that were scaled *closer* to the centroid of the deterministic than the probabilistic solution (i.e., those stimuli with ratio scores ≤ 1.0). We also expected that this effect would be more pronounced for participants in the alcohol condition and potentially absent for participants in the placebo condition because probabilistic and deterministic results should diverge as perceptual variability increases.

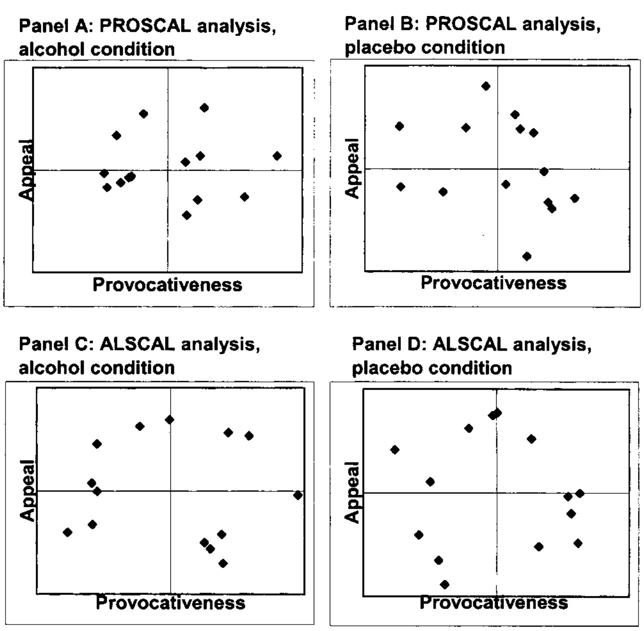

Figure 7. PROSCAL Case III anisotropic group solutions for alcohol (Panel A) and placebo (Panel B) participants; ALSCAL group solutions for alcohol (Panel C) and placebo (Panel D) participants.

Probabilistic and deterministic representations of alcohol participants' data deviated as expected: Stimuli scaled closer to the exterior of the deterministic than the probabilistic solution showed significantly greater variance estimates than stimuli scaled closer to the exterior of the probabilistic than the deterministic solution, $t(12) = 4.84$, $p < .001$, $ES = 2.83$. In contrast, probabilistic and deterministic solutions for placebo participants' data did not differ significantly, and the effect size was much weaker; variance estimates for stimuli scaled closer to the exterior of the deterministic space were more similar to variance estimates for stimuli scaled closer to the exterior of the probabilistic space ($ES = .71$). These results illustrate the impact of inter- and intraindividual perceptual variability on configuration estimation by deterministic methods. ALSCAL placed stimuli farther from the centroid of the space when they were estimated by PROSCAL to have larger variances. Additionally, the magnitude of this effect was greater for alcohol participants, who showed larger variance estimates.

More generally, this example highlights the potential incremental utility of the probabilistic scaling approach under clinically relevant circumstances (see also MacKay & Dröge, 1990, for an alternative applied evaluation of the incremental utility of probabilistic representations of perceptual organization). When marked perceptual variability is present or stimuli are very confusable, probabilistic methods should provide more precise and valid estimates of participants' perceptual organizations. Thus, the researcher, or clinician, has a higher resolution representation of participants' or clients' perceptual organizations at his or her disposal. In contrast, deterministic methods should show a systematic bias toward placing stimuli associated with larger variance estimates closer to the exterior of the psychological space. Thus, if nonnegligible perceptual variability or stimulus confusability is present, probabilistic methods should prove particularly helpful when the investigator is interested in individual differences in intradimensional organization (e.g., when the researcher hopes to distinguish between the upper and lower halves of Figure 3). Additionally, individual differences in the magnitude of the variance estimates may prove to be of intrinsic interest. For example, marked deterioration in precise perception of a woman's sexual interest under the influence of alcohol might place a man at particularly high risk of engaging in sexually coercive behavior.

Thus far, we have examined the use of deterministic and probabilistic MDS methods for characterization of clinically relevant individual differences in perceptual organization. Probabilistic models are preferable in the presence of significant perceptual variability or stimulus confusability, particularly when intradimensional perceptual organization or the magnitude of variance estimates are of primary interest. Under less variable circumstances, however, probabilistic and deterministic solutions converge. In such cases, deterministic techniques are preferable when individual differences are of primary interest, because deterministic methods' treatment of individual differences is more advanced at this point. Thus, readers should consider both options and select the one that is more appropriate to their circumstances.

In our experience, the use of MDS methods to evaluate questions about clinically relevant perceptual organization is limited primarily by logistical and theoretical considerations. Logistically, MDS analysis typically requires the collection of extensive similarity ratings, identification confusions, or same–different judgments. It may be possible to collect a carefully chosen subset of judgments instead, however, particularly when MDS is used in a confirmatory fashion, because fewer parameters must be estimated (MacCallum, 1988; Spence & Domoney, 1974; Zinnes & MacKay, 1983). Theoretically, it is important to avoid assuming that characteristics of MDS solutions are stable across time, context, and stimulus-set modifications. Increasing the variability along the body-size dimension in our stimulus set, for example, would increase our estimates of attention to body size. The tendency toward reification of MDS solutions also is at odds with cognitive psychologists' view of cognitive processing as dynamic and contextualized. Finally, although similarity ratings do not rely on introspective reports about cognitive processing, they nonetheless are subject to presentation biases. Researchers may be able to minimize demand characteristics and discourage deliberative responding by requiring speeded responses or shortening stimulus durations.

Use of the MDS approach is appropriate even when participants cannot provide a valid account of the way in which they process information. Some clinical investigators have moved in the direction of using more performance-based assessment strategies, typically based on the Stroop or dichotic listening paradigms (Bruder, 1991; MacLeod, 1991; Williams, Mathews, & MacLeod, 1996). These methods, however, lack the theoretical coherence of MDS methods, which are part of an extensive set of interrelated measurement models developed by cognitive psychologists to evaluate information processing. In the final section, we address and illustrate the use of MDS methods, in conjunction with formal cognitive process models, to investigate theoretical models of the way in which perceptual organization influences cognitive processing.

Predicting Cognitive Processing From MDS-Derived Representations of Perceptual Organization

A fundamental premise of cognitive psychology is that perceptual organization influences and constrains the operation of other cognitive processes presumably "downstream" from perceptual organization, such as identification, classification, recognition memory, and category learning. Thus, perceptual organization alone does not explain behavior, but rather is only the first step in an unfolding process. One of the primary goals of cognitive psychologists has been the development of formal mathematical models of the mechanisms by which perceptual organization affects these other cognitive processes. For example, Nosofsky, Kruschke, and colleagues have used MDS-derived representations of participants' perceptual organizations successfully to predict performance across independent tasks assessing classification, memory, and learning processes (Kruschke, 1992; Kruschke & Johansen, 1999; Nosofsky, 1986, 1991, 1992a, 1992b; Nosofsky, Kruschke, & McKinley, 1992). Formal mathematical models traditionally have been used to investigate associations among normative performances on tasks assessing these different processes, typically using simple, artificial stimuli. Fortunately, several studies demonstrated that basic information-processing models generalize well to an evaluation of information processing under much less idealized circumstances, in which investigators examine the role of individual differences in information processing (Nosofsky & Zaki, 1998), sometimes with much more complex, socially relevant stimuli (e.g., Carter & Neufeld, 1999; Treat et al., 2001; Viken et al., in press). These studies serve as exemplars of how formal process models, in concert with MDS-based representations of perceptual organization, can be used to make clinically relevant inferences about perceptual organization, the operation of downstream cognitive processes, and the linkages between perceptual organization and these other processes. We describe one study in some detail (Viken et al., in press), but readers also may want to consult Carter and Neufeld (1999), Nosofsky and Zaki (1998), and Treat et al. (2001).

Social information-processing models of eating disorders propose that bulimic behaviors are maintained in part by differential attention to, classification of, memory for, and learning of information related to shape, weight, eating, and food (Vitousek, 1996; Vitousek & Hollon, 1990; Williamson et al., 1999). Thus, bulimics' differential attention to body size and affect in similarity ratings tasks should result in their differential sensitivity to body size and affect in classification tasks. We evaluated this hypothesis formally as a part of the study described earlier (Viken et al., in press). Bulimics and controls first rated the similarity of all possible pairs of 24 stimulus photos of women, who varied along facial-affect and body-size dimensions. Participants next completed two prototype classification tasks (Cohen & Massaro, 1992; Massaro, 1991). In each task, participants first viewed two prototypical stimuli, which varied along both body-size and affect dimensions. In the first task, for example, participants viewed a happy-heavy woman (Prototype A) and an unhappy-light woman (Prototype B). Participants then classified each of the remaining 22 stimuli as Type A or Type B women. Participants could base their classifications on body size, affect, both attributes, or any attribute perceived to differentiate the two prototypes.

To evaluate whether individual differences in perceptual organization predicted individual differences in classification, we fit Nosofsky's (1987) weighted-prototype model of classification to participants' averaged classification judgments. The model specified that the probability of classifying stimulus i as a Type A woman increased as the perceived similarity of i to Prototype A increased, and that similarity was a decreasing function of distance in psychological space. The distance between i and A, d_{iA}, was computed using a weighted Euclidean metric, as in the deterministic MDS models described earlier:

$$d_{iA} = \left[\sum_{m=1}^{2} w_m (x_{im} - x_{Am})^2 \right]^{1/2},$$

where w_m represents the weights for Dimensions 1 (body size) and 2 (affect), which sum to 1.0. Then, the similarity of i to A, η_{iA} was an exponentially decreasing function of d_{iA}:

$$\eta_{iA} = e^{-cd_{iA}},$$

in which c was a scaling parameter that determines the rate at which similarity declines with distance. The classification probabilities, $P(A|i)$, were represented by the weighted similarity of i to A, relative to the sum of the weighted similarities of i to A and i to B:

$$P(A|i) = \frac{\beta_A \eta_{iA}}{\beta_A \eta_{iA} + (1 - \beta_A)\eta_{iB}},$$

where β_A was a response-bias parameter representing relative use of Type A classification responses.

This model potentially could predict differential classification probabilities for bulimics and controls by including group-specific parameter estimates of w_m. An intuitive grasp of the model's predictions can be gained by reinspecting Figure 1. Panels B and C present sample perceptual organizations for BSO and AO participants, respectively. Prototypes A and B are identified on both graphs, and their coordinates differ along both the affect and body-size dimensions. Stimulus *i* is much more similar to (i.e., closer to) Prototype A than Prototype B in the BSO participant's psychological space; the opposite circumstance characterizes the AO participant's representation. Thus, a model containing group-specific estimates of w_m should predict that BSO participants were much more likely to classify stimulus *i* as a Type A woman, and that AO participants were much more likely to classify stimulus *i* as a Type B woman, if no biases toward more frequent use of one response were present.

Results were consistent with these theoretical predictions for both classification tasks when different versions of the model were fit to participants' classification data. All models contained at least three parameters: a single scaling parameter, a single response-bias parameter, and a single attention-weight parameter. Alternative models assumed that one or more of these three parameters was group specific (i.e., estimated separately for bulimics and controls). Thus, the most general model had six parameters. As expected, the best fitting model contained four parameters: a single scaling parameter, a single response-bias parameter, and group-specific attention-weight parameters. Additionally, group-specific estimates of attention weights showed that body size was more salient (hence, affect was less salient) for bulimics than for controls. This model fit significantly better than a three-parameter model, which estimated only scaling, response-bias, and attention-weight parameters, and better than two alternative four-parameter models, which estimated either group-specific scaling or group-specific response-bias parameters.

Nosofsky's (1987) weighted-prototype classification model is but one of many specifying a formal link between an MDS-based representation of perceptual organization and the operation of other cognitive processes. Alternative models, for example, could be used to evaluate the congruence of recognition-memory or category-learning processes with perceptual organization (Kruschke, 1992; Kruschke & Johansen, 1999; Nosofsky, 1986, 1991, 1992a, 1992b). Models such as these have guided our preliminary investigations of whether bulimics show differential memory for and learning of body-size and affect information, compared with controls (Treat, 2000).

Formal modeling strategies allow researchers to test theoretical expectations about the linkage between perceptual organization and cognitive processing in a rigorous and specific fashion. Fitting formal process models should strengthen clinical scientists' inferences about where information processing is going awry and may suggest novel intervention strategies. At a more general level, these strategies also should help us determine whether a single model of human cognition, which allows individual- or group-specific parameter estimates, can provide a sufficient account of both normal and abnormal processing.

Implications for Clinical Assessment and Intervention

Enhancing our understanding of the cognitive mechanisms underlying or covarying with psychopathology ultimately should inform our assessment and intervention strategies with individual clients. Thus, before closing, we briefly speculate about the potential utility of MDS methods and formal process modeling for individualized clinical assessment and treatment. An important preliminary step in this direction entails augmentation of the analytical strategies used in clinical research to allow simultaneous estimation of group- and individual-specific parameters. The deterministic scaling methods discussed earlier (e.g., WMDS and Tucker's correlational approach) already allow this possibility by estimating individual-specific attention weights and dimensional correlations while simultaneously estimating group-specific stimulus coordinates. Probabilistic scaling methods and formal process models could be extended in a similar fashion. This work would allow us to form normative distributions of parameter estimates and to evaluate the relationship between these distributions and aspects of psychopathology.

This hybridization of nomothetic and idiographic research approaches should serve as a useful bridge to more idiographic, but nomothetically informed, applications. Eventually, individual clients might be asked to complete relevant cognitive-performance tasks, such as those described here, as a routine component of both initial and ongoing assessment. Formal modeling of a client's data would provide parameter estimates that could be compared with existing normative data, and the clinician might target or monitor relevant cognitive processes during treatment.

The assessment findings also might suggest novel treatment approaches that capitalize on cognitive psychologists' expertise in modifying cognitive processing. Suppose, for example, that a woman who presented with bulimic symptoms completed at intake a battery of cognitive-performance tasks designed to assess her relative attention to, memory for, and learning of affect and body-size information. Suppose further that her modeled performance was particularly noteworthy in that she attended very little to affective information, which then resulted in poor memory for and learning of affective information. An important initial step in therapy, therefore, might involve training the client to attend more to such information, particularly under conditions associated with an increased likelihood of symptomatic behavior (e.g., after consumption of a taboo food or a negative interpersonal encounter). Similarly, a critical step in the early stages of treating a man who repeatedly exhibited sexually coercive behavior with acquaintances might entail formal training aimed at (a) increasing the accuracy of his perceptions of a woman's level of sexual interest, particularly under high-risk conditions (e.g., while intoxicated or sexually aroused), and (b) decreasing his perceived association between her level of sexual interest and the provocativeness of her dress.

Currently, only promissory notes about such applications are tenable because we simply do not know enough yet about the role of cognitive processing in eating disorders and sexual coercion to capitalize on these opportunities. Nonetheless, we hope to have piqued the reader's interest in these potential applications of MDS methods and formal process modeling for individualized clinical assessment and treatment.

Conclusion

Numerous clinical theories assign a critical role to cognitive processing in the development and maintenance of psychopathology, such as Kelly's (1955) personal construct theory, but measurement models capable of investigating these theories have been lacking. We have argued that MDS techniques provide a promising method of characterizing clinically relevant individual differences in perceptual organization. Here we focused on the characteristics of dimensional attention, perceptual correlation, within-attribute organization, and perceptual variability. Additionally, we have suggested that process models can be used in conjunction with MDS-derived representations of perceptual organization to illuminate the role of construal processes in the operation of downstream cognitive processes. Using the theoretical and measurement models drawn from cognitive science to evaluate the role of cognition in psychopathology is an important step toward bridging the gap that has separated basic and applied work on human cognition (McFall et al., 1997, 1998). These bridging efforts are likely to prove mutually beneficial to clinical and cognitive scientists. They simultaneously should increase the strength of clinical scientists' inferences about cognitive influences on psychopathology (Platt, 1964), while enhancing the relevance of cognitive scientists' theories and methods to real-world problems.

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